Visible Light Communications for Indoor Monitoring (VLADIMIR)

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ABSTRACT

VLADIMIR is an ATTRACT Phase 1 project that showed the feasibility of monitoring the status of an indoor environment by sensing the *optical signature* that an object creates on a Visible Light Communication (VLC) signal. The Channel State Information that a VLC receiver computes for data detection was also utilized to train a Machine Learning classifier used for monitoring. The performance evaluation of the experimental VLC-based monitoring demo achieved a positioning accuracy in the few-centimeter-range, without the necessity of deploying a large number of sensors in the room and/or adding a VLC-enabled sensor on the object to-be-tracked. The core importance that a continuation of VLADIMIR project will have in ATTRACT Phase 2 is also discussed in detail.

Keywords: Visible Light Communications; Phosphor-converted LED; Photodetector; Monitoring; Machine Learning; Illumination.

1. INTRODUCTION

Activity recognition has gained notable attention lately for the large number of applications that should monitor the movement of humans to carry out their tasks. These applications include, *e.g.*, health monitoring, fall detection of elderly people, detection of intruders, estimation of room occupancy rate, *etc.* Traditionally, activity recognition relies on the information collected from wearable sensors (accelerometers and gyroscopes) or cameras that continuously take readings or pictures. However, these methods have drawbacks related to the energy consumption, infrastructure costs and generate serious concerns on users' privacy. This is the reason why the utilization of wireless communication signal for activity recognition represents an interesting option, as the infrastructure for sensing would be already deployed, and the users' private information is never exposed.

Visible Light Communication (VLC) technology tackles most of the drawbacks that monitoring systems based on Radio Frequency (RF) communications have. For example, since VLC beams cannot propagate through opaque obstacles such as walls or curtains, they can be easily confined into the designated coverage area to enable secured communication links. In addition, though VLC uses a portion of the electromagnetic spectrum that is licence-free, it enables the ultra-dense deployment of co-located low-interference beams using directive spot-lights. Thanks to this, the stability of the communication link increases, and it is possible to detect minor changes on the received optical signal, which enables a better activity recognition accuracy when compared to RF-based solutions. Moreover, the same infrastructure for illumination and communication can be also re-used for VLC-based monitoring. Finally, VLC technology can be utilized in places such as hospitals, where RF systems are banned due to Electromagnetic Compatibility problems.

VLADIMIR proved that it is feasible to implement a VLC-based monitoring system in which the presence and/or position of an object can be accurately identified using Machine Learning (ML). More precisely, a software-defined Optical OFDM transmission was implemented using commercial phosphor-converted LED and Photodetector. The ML classifier that monitored the status of the experimental demo was trained with the Channel State Information (CSI) of the VLC link when the target object took different positions. The good accuracy that the proof-of-concept for VLC-based monitoring showed paves the way for its utilization in scenarios where video cameras and/or RF-based monitoring cannot be used for different reasons.

2. STATE-OF-THE-ART

Camera-based surveillance systems can be used indoors or outdoors; however, they require a Line-of-Sight perimeter to-be-monitored and may contravene individuals' privacy if video images are not protected **[1].** Besides, ubiquitous availability of Wi-Fi access points, particularly indoors, encourages to use of RF-based monitoring by sensing the variations that these radio signals experience. For instance, a ML approach that identified the correlations between the number of people in a room and the CSI collected from co-located Wi-Fi nodes was presented in **[2]**. Similar solutions were proposed for behavior recognition in **[3]**, for personal identification in **[4]** and for motion detection in **[5]**.

Concerning positioning systems, different technologies using wireless signals on different portions of the electromagnetic spectrum have been developed. From them, Global Navigation Satellite Systems (GNSS) such as GPS or Galileo have been mostly used in outdoor applications, whereas positioning systems that sense RF signals coming from Wi-Fi, Bluetooth and/or RFID

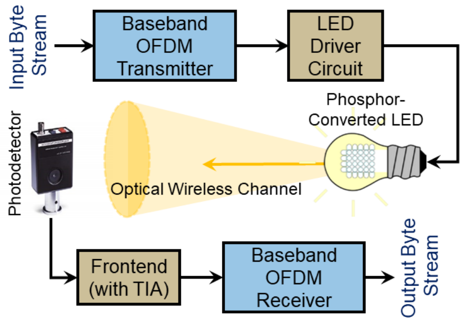

Fig. 1. Block diagram of the VLC demo consisting of an OFDM transmitter with Phosphor-Converted LED, optical wireless channel, and OFDM receiver with PD and TIA.

devices have been mainly proposed for indoors **[6]**. The accuracy of an indoor positioning system depends on the density of signalling nodes. Therefore, if visible light signals were used for this purpose, the infrastructure to perform this task would be already deployed for illumination in each room. Furthermore, visible light-based positioning benefits from the rapid development of low-cost, high-sensitivity photodetector technology that can now detect very small signal variations **[7]**.

Finally, most State-of-the-Art (SotA) solutions based on visible light technology require a sensor on the object to-be-tracked. Then, by measuring the optical power that reaches the Photodetector (PD), it is possible to extract relevant metrics to estimate the location of the object. Examples of these metrics are Angle-of-Arrival (AoA), Received Signal Strength (RSS), Time-of-Arrival (ToA), and Time-Difference-of-Arrival (TDoA) **[8]**.

3. BREAKTHROUGH CHARACTER OF THE PROJECT

The use of RF signals to identify peoples' motion has typically an accuracy of about one meter; unfortunately, such level of precision is not enough to identify multiple objects located in proximity. However, if the carrier frequency moves up into the visible light portion of the electromagnetic spectrum (*e.g.*, between 430-770 THz), a much wider communication bandwidth becomes available. This way, the frequency-selective behaviour of the optical wireless channel can be exploited to extract useful information on the indoor area status. Moreover, the highly directive properties of VLC transmitters, as well as the strong attenuation/absorption that optical wireless signals experience when propagating, minimize the interference between the LED lamps deployed in the same room. Finally, there are also scenarios in which the *intensive* use of RF communication systems is not recommended or even prohibited (*e.g.*, in hospitals, health-care centres, nursery schools) for Electromagnetic Compatibility and/or raising concerns that society has about the effects that long-exposure to RF radiation may have on babies and young children under three years.

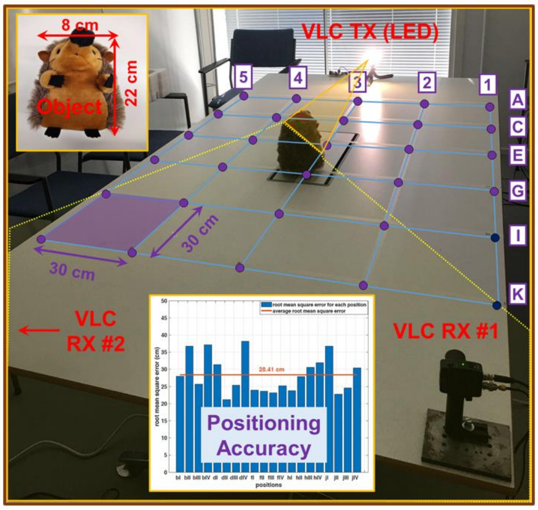

Fig. 2. Picture of the actual setting used in the experimental evaluation. The object that was used to identify its position on the table was a stuffed toy (brown hedgehog). The points labeled with letters (rows) and numbers (columns) are the positions used in the training phase.

The better sensing accuracy of VLC-based monitoring, when compared to their RF counterparts, stem from:

(a) Multi-path propagation. The indoor propagation of VLC signals is dominated by the direct Line-of-Sight link between transmitter and receiver. Therefore, the optical power that is reflected-back when VLC signals interact with large objects is notable weaker than the incident power. This is not the case of Wi-Fi signals, in which strong reflections complicate the extraction of useful patterns from the received signal samples.

(b) Co-channel interference. VLC signals can be easily blocked by opaque obstacles such as walls or curtains; due to that, it is very easy to confine the data-carrying signal into the target sensing area, controlling the background inter-cell interference. Moreover, directive light beams can be constructed using spot-light fixtures, complicating the attack of a hypothetical eavesdropper.

(c) Wireless carrier wavelength. The much shorter wavelength of the VLC carriers enables the detection of smaller changes/variations on the status of the room. Note that 'λ_{VLC}' is between 400 and 700 nm, whereas '$\lambda_{Wi\text{-}Fi}$' equals 12.5 cm for the 2.4 GHz ISM band.

(d) Reutilization of existing infrastructure: VLC-based monitoring makes use of LED lamps for multiple tasks: Communication, Sensing and Illumination. Common deployments rely on direct illumination, but indirect illumination in which the PD receives the reflected light from the (white) ceiling are also possible to verify the illumination constraints **[9, 10]**.

4. PROJECT RESULTS

The block diagram of the simplified VLC system that was used to validate the indoor monitoring concept of VLADIMIR is shown in Fig. 1 **[11]**. It consists of an

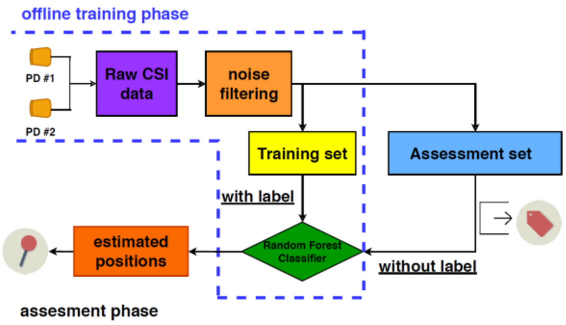

Fig. 3. Block diagram of the process used to evaluate the accuracy of proposed VLC-based monitoring solution. The input CSI samples with labels (known positions) are used to train offline the ML classifier, whereas the unlabeled CSI inputs are used in the online assessment phase to estimate the position of the object.

input sequence of bytes, a software-defined baseband OFDM transmitter, and an LED driver circuit that adapts the output voltage of the Universal Software Radio Peripheral (USRP) to the input current that drives an LED array of 7 LUXEON Rebel Plus LX18-P140-3 (Neutral white light - 4000 K). At the receiver side, the PDA100A2 PD from Thorlabs is utilized, which includes an embedded Trans-Impedance Amplifier (TIA) that adapts the weak output current of the PD to the voltage input of the USRP, before the signal processing for baseband OFDM reception is performed.

The practical validation of the VLC-based monitoring concept was done on a controlled experimental setting, which resembles the one found in a realistic indoor environment after a proper dimension-scaling. In this setup, an array of Phosphor-Converted LEDs and two PDs are placed on the opposite sides of a meeting-room table of size 2.4 m x 1.2 m, as illustrated in Fig. 2. In the central part of the table, a grid with 5 x 4 square elements of size 30 cm x 30 cm is marked (solid blue lines), creating 30 equal-separated positions that are used to train the ML classifiers (solid blue points). Finally, the center of each of these square elements are used for assessing the performance of the trained classifier.

The object-to-be-monitored, which is placed between the LED and PD, creates a *signature* on the CSI amplitudes that the ML classifier will be trained to identify it. The overview ML algorithm that is used to perform the VLC-based monitoring is shown in Fig. 3, where the *offline training* and the *online assessment* phases of the ML classifier are identified. During the training phase, the ML classifier identifies hidden patterns on the collected CSI sequences when the object takes different positions, using the labels that are included in the measurements to implement the supervised learning strategy. In this context, the training ratio is the fraction of the whole data, collected from measurements, which is used for training; remaining data are used for assessment **[12]**.

The performance assessment of the proposed VLC-based monitoring solution considers two situations: On one hand *Case-1*, where the CSI collected from the 30 training positions (solid blue points in Fig. 2) are used in the construction (offline training) and in the evaluation (online assessment) of the ML classifier. On the other hand is *Case-2*, where the performance of the trained ML classifier is evaluated utilizing the CSI that is collected when the object takes any of the 20 new positions for assessment (center of blue squares in Fig. 2).

"Actual Positions" \ "Estimated Positions"	No Object	A3	C3	E3	G3	I3	K3
No Object	0,999	0.00	0.00	0,0002	0,0007	0.00	0.00
A3	0.0004	0,999	0.00	0.00	0.00	0.00	0.00
C3	0,0005	0.00	0,995	0.00	0.00	0.00	0.00
E3	0,0001	0.00	0.00	0,992	0.00	0.00	0.00
G3	0.00	0.00	0.00	0.00	0,995	0.00	0.00
I3	0,0001	0.00	0.00	0.00	0.00	0,992	0.00
K3	0,0001	0.00	0.00	0.00	0.00	0.00	0,997

(a)

"Actual Positions" \ "Estimated Positions"	No Object	E1	E2	E3	E4	E5
No Object	0,999	0.00	0,0003	0.00	0.00	0.00
E1	0,00088	0,9991	0.00	0.00	0.00	0.00
E2	0,0002	0.00	0,9993	0.00	0.00	0.00
E3	0,0004	0.00	0.00	0,9995	0.00	0.00
E4	0,0006	0.00	0.00	0.00	0,9993	0.00
E5	0,001	0.00	0.00	0.00	0.00	0,9986

(b)

Fig. 4. Confusion matrices of the ML classifier used in the proposed VLC-based monitoring solution for a 70% training ratio. (a) The object takes positions on column 3. (b) The object takes position on row E.

In order to assess the performance of the ML classifier, both confusion matrices and Root Mean Square (RMS) positioning errors are considered. Confusion matrices are widely used to indicate the accuracy of a given classifier. In a confusion matrix, the values stored in the main diagonal corresponds to the probability of making good predictions, whereas the off-diagonal values identify the probability of making wrong predictions. Since it is not practical to visualize the 30 x 30 confusion matrix that corresponds to all possible values in *Case-1*, a subset of them has been selected for visualization in Fig 4.

Based on the confusion values for locations in column 3 (upper table) and row E (lower table), it is possible to see that the ML classifier can identify the presence and position of the object correctly in more than 98% of the cases. Similar hitting probabilities were observed in the remaining rows and columns. Finally, according to the RMS errors reported in Fig. 2, we conclude that the ML classifier has a positioning accuracy that is in the range of the separation that exists between points in the training phase (*i.e.*, less than 30 cm on average). If better positioning accuracy is desired, the ML classifier should be trained with more densely-packed training points.

5. FUTURE PROJECT VISION

VLADIMIR proved that apart from communications and illumination, VLC technology can also be used to monitor the status of an indoor environment. Next steps to move forward in the maturity level of the technology is to carry out intensive experimentations, starting from controlled laboratory setting and continuing in actual scenarios that are closer to the practical application.

5.1. Technology Scaling

The *know how* to implement a monitoring system based on VLC technology is already mastered (TRL 1-3). To scale up the TRL of this indoor monitoring innovation, advanced demonstrations and prototype developments are needed to validate an actual application of this concept in intended/real-world scenarios (TRL 4-6). For this purpose, three different lines of actions are proposed:

● **Innovative applications enabled by VLC**. Deals with the identification of new applications and, based on them, the definition of the problem to be addressed by using simultaneously the data transmission, sensing and illumination features of VLC technology. The details of the environment setting, as well as the target goals, will be defined in collaboration with advisors with expertise on illumination and context-aware applications. The innovations with highest potential should be selected for practical experimentation, considering the advice of communications and signal processing collaborators.

● **Demonstration of VLC-based innovations**. Deals with the implementation, integration and testing of the different communication, sensing and illumination discrete components into an experimental hardware platform. The transmission scheme for VLC will be selected to provide: (a) An acceptable data rate with respect to contemporary figures of merits; (b) Possibility to adjust the illuminance and chromaticity of the aggregate white light that is generated when using tri-color LEDs in a range to-be-defined; (c) Appealing optical waveform features to obtain a good accuracy when the same VLC signal is used for monitoring.

● **Maturity development of VLC-based innovation.** Deals with the construction of a prototype to carry out an extensive measurement campaign, in order to collect relevant information of the optical signature that is created on the VLC signal, and to classify it to identify the target event that is relevant for the innovation. Aim is to perform a rigorous testing of the application in relevant environments, providing useful information to develop the level of maturity of the innovative concept.

5.2. Project Synergies and Outreach

Current consortium will have to be reinforced, in order to achieve a deeper level of maturity in the VLADIMIR concept (TRL 5-7). For this purpose, it would be good to identify new partners that would complement the *know-how* that is currently mastered in three main directions:

- **System-on-Chip prototyping.** Implementation of the signal processing algorithms needed for VLC-based monitoring on a hardware platform that could be easily installed in the relevant operational environment.
- **Innovative applications.** Identification of applications in which the communications, sensing and illumination features the VLC technology can be complementary used to innovate and/or address the shortcoming that current Sot solutions based on radio signals have.
- **Semiconductor technology.** So far, commercial LEDs and PDs have been used. To sale up on the TRL, better quality semiconductors are needed to sense more accurately the unique *signature* that an object creates when placed between VLC transmitter and receiver.

Concerning the public engagement strategy, aim is to become involved in the following activities:

- **Social and mass media:** Dedicated social media channels, such as *Linked-in*, *Twitter* and *Facebook*, will be used to communicate the Research, Development and Innovation (RDI) activities and news. *YouTube* video links will be shared on social media and project website. Interviews in newspaper, radio and local/national TV programs will be searched.
- **Public talks:** Aim will be to showcase the project activities to general audiences and specialized environments (*e.g.*, University science fairs), and in talks to undergraduate students and in High Schools.
- **Industrial Congresses:** Project activities will be promoted in relevant industrial-oriented congresses, and participation in 5G global events will be seek.

5.3. Technology application and demonstration cases

The technology demonstration cases to be implemented in ATTRACT Phase 2 will take advantage of the following unique features of VLC technology, namely:

1. The extremely wide bandwidth that VLC signals occupy, enabling a much better sensing accuracy than SotA solutions based on radio communications, as much more diverse information can be collected.
2. The intensity and chromaticity of the illumination that the VLC system provides, which can be adjusted to improve the occupants' well-being, without affecting the quality of the offered data services.
3. VLC technology is economical when compared to high-frequency radio (mmWave and Tera-Hertz). Thus, VLC technology has potential to become a mainstream for ultra-dense deployments in 5G+.

Novel applications of VLC technology will speed-up its adoption, taking advantage of the benefits that this technology already offers (*i.e.*, license-free spectrum, easy-to-control interference, security, low-cost, *etc.*), but also enabling new smart services without the necessity of deploying new infrastructure for sensing/illumination. This technology demonstration will bring benefits in:

- **Scientific Research:** Unique multi-disciplinary research opportunity, combining concepts from communications, illumination and sensing technology.
- **Industry:** Promote creation of start-ups exploiting novel concepts enabled by VLC technology, as investment to work on visible light spectrum is more modest that the one needed in *mmWave* bands.

- **Societal Challenges:** Address major concerns shared by citizens, such as health and well-being (*e.g.*, fall detection of elderly people), efficient use of energy (*e.g.*, smart heating and illumination), secure societies (*e.g.*, non-invasive monitoring), *etc.*

5.4. Technology commercialization

Before commercialization, concrete applications of the VLC-based monitoring concept of VLADIMIR will be identified. After that, potential investors will be contacted by participating in relevant industrial-oriented events, getting in the entrepreneurial community (e.g., Aalto University Design factory), contacting lobbying organisations for technology industry companies, and looking for angel investors networks that may be interested to invest in the innovation.

Moreover, private/public sources of funding, such as *Seed Funding* for strategic research ideas (promoting multi-disciplinary collaboration among research groups to build ecosystems) and funding calls for *Projects Preparing the Commercialization* of research-based idea (promoting its development as a new business once technology development is matured) will be seek.

5.5. Envisioned risks

Two main technical risks have been identified for an ATTRACT Phase 2 participation of VLADMIR project:

1. *VLC-based monitoring using commercial LEDs/ PDs provides not satisfactory data rate, illumination or sensing performance.* Mitigation strategy: Replace critical commercial components with application-specific ones, in which the technical characteristics are better optimised for the target figure of merit.
2. *Delay/failure in the development of communication, sensing and illumination components.* Mitigation strategy: Collaborators with complementary expertise will be selected for each project objective, providing redundancy and offering alternative approaches to maximise chances of success.

5.6. Liaison with Student Teams and Socio-Economic studies

In an ATTRACT Phase 2 participation, young people outreach days will be organized by VLADIMIR not only at Universities (MSc-level), but also in high-schools. During these events, the key project outcomes will be communicated with a level of detail for non-specialists.

Moreover, sprint-like events (hackathon) and/or longer events involving project-based learning will be arranged. In these activities, groups of about four students with complementary expertise will collaborate intensively to address some challenge that industry collaborators identify for VLC-based monitoring applications.

Participation in expert-driven socio-economic study of the ATTRACT initiative and ecosystem will be also promoted, contributing actively with information that is needed to these studies (*e.g.* interviews, technology impact references, among others).

6. ACKNOWLEDGEMENT

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