# Comparison of clustering algorithms for data detection in Multispectral Camera Communication

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***Abstract*—In this work, the performance of an optical camera communication (OCC) system is compared using several clustering algorithms in a cluster-based data detection approach. Furthermore, a multispectral camera is utilized to capture the thermally induced spectral variations in light-emitting diodes (LEDs). Thus, more than one channel can be attained from the same device. The results of this paper prove that using a clustering method can enhance the bit error rate (BER). Finally, different training sets were used to fit the clustering models underlining the impact on the system performance.**

***Index Terms*—Clustering, optical camera communication, multispectral, temperature effect.**

## I. Introduction

OPTICAL wireless communications (OWC) are believed to be a crucial technology in future wireless communication systems. Besides, as part of the OWC, optical camera communication (OCC) has attracted increasing interest in recent years due to the advances in cameras and image sensors and their ubiquity on consumer electronics devices [1].

For this reason, the last few years have witnessed enormous growth in OCC systems. However, a challenging area in this field is the maximum achievable data rate limited by the camera's scanning method. Therefore, several studies have tended to focus on increasing data rate. For example, in [2], Arai *et al.* improved the data rate of an image sensor communication (ISC) system by designing a rotary light-emitting diode (LED) transmitter that rotates the blinking LEDs during the camera's exposure time. Thus, the camera captures the different LED states as afterimages, increasing the data rate 60 times more than using a conventional ISC system.

It is well-known that temperature has a significant impact on LED devices. Many studies have examined the thermal effects on light sources caused by the LED's p-n junction temperature alterations [3], [4]. One of the most important effects to take into consideration in OWC is the spectral emission variation. Varshni and Planck-Einstein's relations show that the peak wavelength rises with temperature in general. However, few researchers have addressed this impact and found that it degrades system performance [5], [6].

Nonetheless, recent studies have focused on using this hypothetical negative effect to expand the number of communication channels. A multispectral camera with appropriate spectral resolution to discern the spectral signatures of LEDs at different temperatures could be used to achieve this enhancement [7], [8].

On the other hand, machine-learning-based techniques are gaining popularity in communication systems. Due to recent insights about unsupervised learning, the performance of OWC systems has improved. For instance, Wu and Chi boosted the data rate of an underwater visible light communication (VLC) system to 75 Mbps by correcting the phase deviation of 8-quadrature amplitude modulation (QAM) with a k-means algorithm [9]. In a VLC system based on direct current biased optical orthogonal frequency-division multiplexing (DCO-OFDM), Wang *et al.* used a k-medoids method. The clustering technique was used in the post-equalization step to minimize noise and identify distorted constellation points, improving the system's bit error rate (BER) [10].

Furthermore, Ma *et al.* used a k-means clustering technique to decrease nonlinear distortion effects in a VLC system with Nyquist pulse-amplitude modulation (PAM), significantly enhancing the BER performance over earlier studies [11]. Finally, Shi *et al.* used a density-based spatial clustering of applications with noise (DBSCAN) method in a PAM-7 multiple-input single-output (MISO) underwater VLC system in [12]. DBSCAN was utilized in their proposal to overcome the problem of incorrect assignation caused by the mismatch between the two LEDs used in the transmission.

Similarly, some research has proposed machine learning approaches based on neural networks (NN) to minimize inter-symbol interference (ISI) in rolling shutter image sensors evoked by the pixel-row exposure delay [13], [14].

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This paper employs several clustering algorithms to obtain the individual signals from two LEDs with distinct thermally induced spectral characteristics in a multispectral camera communication (MCC) system. The multispectral camera has the spectral resolution required to detect changes in the LED's spectral response caused by temperature variations in the p-n junction. In addition, each transmitter has a different spectral signature at different temperatures; therefore, various communication channels can be established using the same transmitter device. As a result, a multispectral camera that can differentiate signals with distinguishable spectral features permits the use of a temperature-based spectral signature multiplexing technique. Lastly, a cluster analysis using different clustering models is conducted, and the system performance is evaluated.

In this work, the proposed methodology to perform the experiment is described in Section II. Then, Section III presents the obtained results from the methodology and compares the performance of the clustering algorithms. Lastly, some conclusions are drawn in Section IV.

## II. Methodology

The main aim of this work is to experimentally test the performance of a multispectral camera (MS) in a communication link (LED-to-camera) using different clustering algorithms. Besides, in order to take advantage of the high-spectral-resolution capability of this kind of camera, LEDs of a specific wavelength have been employed at different driving currents to modify their working temperature and get different spectral signatures that the MS camera can detect. Furthermore, a cluster-based data detection procedure has been utilized. Some of the most popular types of clustering algorithms were used (hierarchical clustering, centroid-based clustering, and distribution-based clustering) to examine their performance for OCC when different training sets were employed. An in-depth analysis of the algorithms was not performed as it was beyond the scope of this paper.

Two red LEDs were used as transmitters in the system based on the fact that those devices achieved the best results in [8]. The driving current of each LED was controlled by a circuit supplied by a voltage source. Besides, each circuit was connected to a micro-controller that generated a variable pulse position modulation (VPPM) signal depending on the desired temperature to be induced in the LED due to the Joule effect. Finally, the micro-controller devices were connected through the serial port to be controlled by the personal computer (PC), which sent the transmitted data.

On the other hand, the MS camera was connected to the PC via Ethernet in order to manage the capturing process. In addition, a diffuser between the LEDs and the camera was placed to mix the light beams and avoid saturation in the camera. All the setup was located inside a dark chamber to reduce background-light interference. Finally, a Python-based automation script was developed to coordinate all the processes and communicate to the micro-controller devices and the camera.

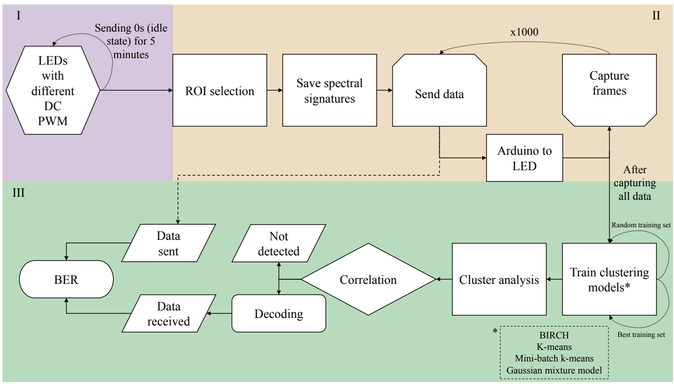



Fig. 1. Flowchart of the experimental procedures. It is split into three phases: Phase I: LED temperature stabilization. Phase II: transmission and reception. Phase III: cluster analysis and performance evaluation.

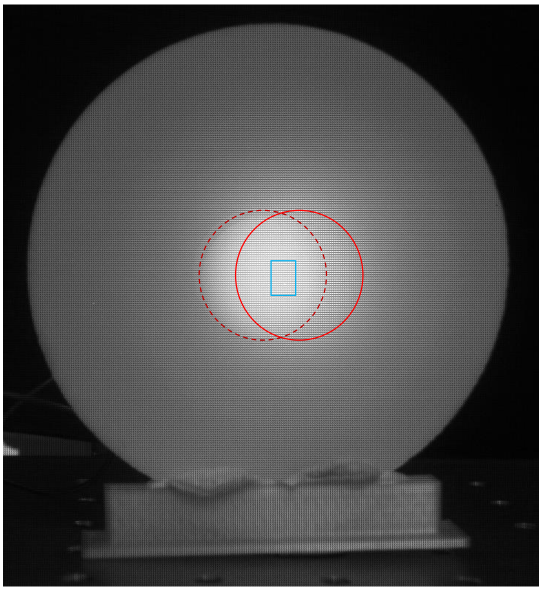


Fig. 2. Example of ROI selection. The red circles represent the LED's light beams. The blue square corresponds to the ROI, which is selected in the region where the beams are mixed.

The core of this experiment consisted of using two LEDs of the same model and changing their p-n junction temperature by the Joule effect to reach different spectral responses. Thus, each LED had a specific spectral signature that an MS camera could capture. Furthermore, in order to have those different signatures, each LED had distinct pulse-width modulation (PWM) duty cycle (DC) values so that the higher the DC value, the higher the junction temperature. No thermal management techniques, such as heat sinks, were used in this work, as they would reduce the variation of the LED spectral characteristics. Once the desired temperature was reached, the data transmission started, and the camera captured the images. Finally, a cluster-based data detection approach was carried out, and the system's performance was assessed. Taking the aforementioned explanation into account, the experiment consisted of three main phases, as shown in Fig. 1.

In Phase I, the goal was to achieve a different LED p-n junction temperature in each device. Therefore, the LEDs were set with 30% and 70% DC values. The frequency of the PWM was set to 5 Hz (bit interval of 200 ms), resulting in one symbol every ten frames since the frame rate was 50 fps. With the purpose of reaching the thermal steady-state on the LEDs, the transmitters were set to an idle state for 5 minutes before sending data because no external thermal management technique was applied to stabilize the temperature. It consisted of keeping the LEDs sending a binary zero with the corresponding DC.

Afterward, in Phase II, the region of interest (ROI), where the light beams of the LEDs were mixed, was determined (Fig. 2). Then, the spectral signatures were stored, and the transmission began. The data transmission involved the following steps. In the first place, a list of 1000 8-bit data was generated for each transmitter. Next, each element in each list was sent to the micro-controller devices in byte format. However, in the micro-controller part, the generated bit sequence was encoded in 8B/10B.

Furthermore, due to the sensitivity of the spectral signature to temperature, it was essential to avoid long sequences of "1" or "0". Therefore, the applied encoding allowed the use of a header consisting of non-consecutive zeros and ones. Moreover, the same header was added after the payload to improve the frame-detection process.

Lastly, Phase III involved cluster analysis and the system performance evaluation. First, several clustering algorithms were used to generate different models and then compare their performance. The employed algorithms were balanced iterative reducing and clustering hierarchies (BIRCH), k-means, mini-batch k-means, and Gaussian mixture model (GMM) [15].

Two distinct strategies were used to train each model. On the one hand, random groups of ten bit streams from the received frames were used to train them. On the other hand, the best set was selected based on the bit error rate (BER) assessment from numerous randomly generated training sets. Once the models were fit according to the training set, they were used to assign a cluster to each sample from the received bit streams. Next, each cluster was assigned to a corresponding symbol (00, 01, 10, or 11) as listed in Table I, obtaining the two LED signals. Subsequently, the resulting signals were correlated (Pearson correlation function) with a matrix comprising all available transmitted signals (a total of $2^{\text{bits}}$). Finally, the maximum correlation value was taken and compared to thresholds from 0 to 0.95 in steps of 0.05. If the maximum value was less than the threshold, the bit stream was considered undetected. Otherwise, the BER is evaluated by decoding the received signal and comparing it to the transmitted signal. This process was repeated for each clustering model. Table II describes the key parameters of the experiment.

TABLE I
CLUSTER INTERPRETATION.

| Symbol | LED state |
|---|---|
| 00 | both LEDs OFF |
| 01<br>10 | one LED ON, one LED OFF |
| 11 | both LEDs ON |

TABLE II
EXPERIMENT KEY PARAMETERS.

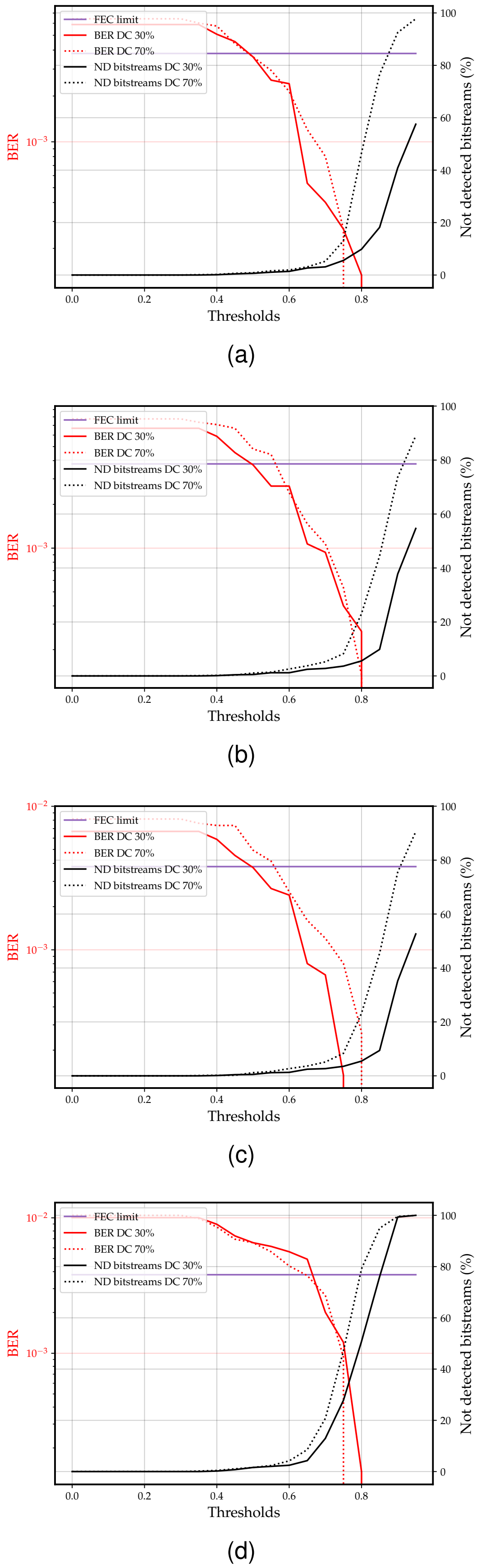
| Parameter | Value |
|---|---|
| | Transmitter |
| Light source | Kingbright L-53SRC-C (Red) |
| Dominant wavelength [nm] | 660 |
| Control device | Arduino UNO |
| | Receiver |
| Camera | SILIOS Technologies CMS-C1-C-EVR1M-GigE |
| Resolution [px] | 1280 × 1024 (raw image)<br>426 × 339 (multispectral images) |
| Band's center wavelength [nm] | B1: 424<br>B2: 464<br>B3: 504<br>B4: 544<br>B5: 573<br>B6: 614<br>B7: 656<br>B8: 699<br>B9: 400-800 (pan) |
| Exposure time [ms] | 20 |
| Aperture | f/2.4 |
| Frame rate [fps] | 50 |
| Shutter mode | Global shutter |
| | Bit stream |
| Coding | 8B/10B |
| Modulation | VPPM |
| Bit time [ms] | 200 |
| Duty cycle | 30%, 70% |
| Bits | Header: 10<br>Payload: 8<br>Footer: 10 |
| | Clustering |
| Algorithms | BIRCH (hierarchical CL)<br>K-means, mini-batch k-means (centroid-based CL)<br>Gaussian mixture model (distribution-based CL) |
| Number of clusters | 4 |

## III. RESULTS

In this section, the system performance using several clustering algorithms is analyzed. Figs. 3 and 4 present a comparison of the distinct models trained with the best training set and with random sets, respectively.

It can be seen that the system performance for each model was similar, achieving slightly better results with the BIRCH algorithm (Figs. 3a and 4a). On the contrary, the GMM model (Figs. 3d and 4d) had a poor performance, especially by not detecting considerable bit streams than the other models for BER below the FEC limit ($3.8 \cdot 10^{-3}$).

Regarding the training sets employed to fit the models, only BIRCH and mini-batch k-means algorithms obtained acceptable results (Figs. 4a and 4c). However, the used training set considerably marred the other models' performance (Figs. 4b and 4d).



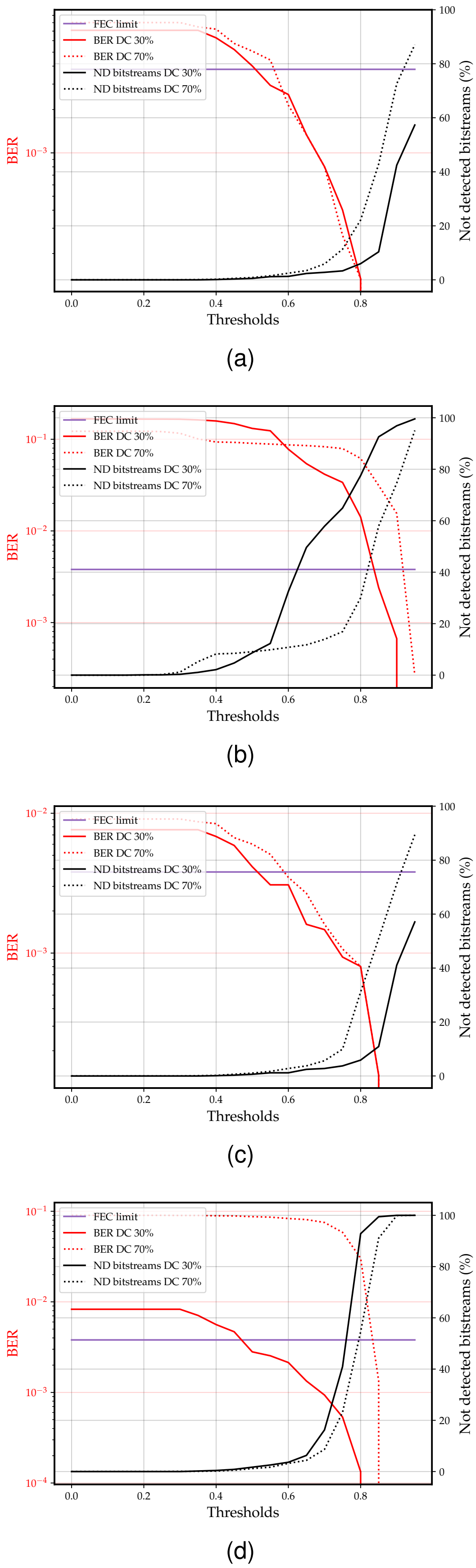




Fig. 3. BER and undetected bit streams at different correlation thresholds using (a) BIRCH, (b) k-means, (c) mini-batch k-means, and (d) GMM algorithms, training the clustering models with the best training set. Solid and dotted lines correspond to the LEDs working at 30% and 70% DC values, respectively.

Fig. 4. BER and undetected bit streams at different correlation thresholds using (a) BIRCH, (b) k-means, (c) mini-batch k-means, and (d) GMM algorithms, training the clustering models with a random training set. Solid and dotted lines correspond to the LEDs working at 30% and 70% DC values, respectively.

## IV. Conclusion

In this work, a cluster-based data detection approach has been utilized in an MCC system. Besides, the effect of temperature on LED has been used to achieve more than one communication channel from the same device. Therefore, different spectral signatures are obtained from the same light source at different temperatures, allowing the MS camera to distinguish the spectral variation. Moreover, several clustering algorithms were used to analyze the system performance. Finally, the different models were fit by employing distinct training sets: on the one hand, a random group of the bit streams; on the other hand, the best combination of bit streams based on the evaluated BER.

The findings of this study indicate that exploiting the thermally induced spectral variations on LEDs and the use of an MS camera allow getting up to two channels from the same light source.

Furthermore, this paper reinforces the usefulness of unsupervised learning methods in OCC systems. Satisfactory results have been obtained, proving that BER below the FEC limit can be achieved. Moreover, the results of this work underline the importance of selecting a proper training set in the clustering model for obtaining satisfactory performance. Similar outcomes were achieved with the BIRCH, k-means, and mini-batch k-means algorithms. However, the GMM model did not have a successful performance, suggesting a non-Gaussian nature of the data. Those cases where the random training set obtained poor results intimate that the bit streams used to fit the model did not correctly represent the sample set.

Further work will concentrate on in-depth analyzing the algorithms and fine-tuning their parameters.

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