Demo: A Context Aware Algorithm for an Adaptive Visible Light Communication System

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Abstract

In this work we propose a context-aware and adaptive Visible Light Communication (VLC) system, able to dynamically react to the environmental changes in order to keep a good communication quality. In particular, we focus on a frame synchronization technique implemented by appending a preamble (repetitive insertion of sequences) to the transmitted data. The size N (number of bits) of the preamble impacts on the performance of the communication system. A short dimension of the preamble is to be preferred to reduce the control overhead (i.e. it is not carrying data information) but it could be not sufficient to perform a good carrier recovery in the case of noisy environmental conditions. This aspect has been modeled as a multi-arm bandit problem and a Thompson Sampling approach is used to find the best value of N for each next transmission frame. Experimental results show the impact played by a correct choice of the parameter N on the reduction of the recovered carrier frequency variance and Bit Error Ratio (BER) in different environmental conditions.

1 Introduction

Recently, Visible Light Communication systems have gained a lot of attention and several new challenges in respect of traditional communication systems need to be identified and addressed in order to make this technology pervasive and ubiquitous as it is in its potentiality [1] [2]. Despite to this success, there are still several challenges that need to be correctly identified and addressed. In this work, we propose an adpative context-aware system, to dynamically compute the length of preamble of transmitted data. To show the approach flexibility, the algorithm has been implemented on a couple of low cost VLC prototypes consisting in an Arduino board, a driving circuit and a led array in the transmitter, a photo-diode, a trans-impedance amplifier and a second Arduino board in the receiver, including a proper ”Virtual Instrument”, developed using the commercial software LabView. Since different conditions need different values of preamble length, the system must be able to gather information about its environment at any given time and adapt its behaviors accordingly (context awareness). Based on these premises, we propose a dynamic computation of N as ideal size of preamble for carrier recovery by modeling it as a multi-arm bandit problem and apply Thompson sampling to select in a fast and efficient way the best value of N [3]. An agent tries to achieve as much award as possible by playing the most rewarding arm among J arms (being J the possible choices of the size N, in a limited sub-set). Each arm rewards randomly upon being played according to an unknown distribution. Our goal is the minimization of the exploration to find the most rewarding arm. The learning approach has been implemented to the receiver side. We assumed that after the receiver computes the ideal value of N, it communicates this value to the transmitter that will consequently adapt the next frame.

2 System and Algorithm Description

Let'us consider the agent A as the algorithm defining the actions performed by an agent based on previous observations. In particular, we assume n_j as the number of times j^{th} arm (the size of preamble) has played after n steps and μ_j to be expected reward of j^{th} arm. The preamble size N is found in average $\mu_j n_j$ times in n_j measurements. In order to reduce errors due to a variation of the recovered carrier, the criterion trigger we apply is based on a real time Bit Error Ratio measurement in the receiving stage. Moreover, the evaluation of the variance ${\sigma_{fi}}^2$ of the carrier detected frequency in output to the phase locked loop after the i^{th} received frame, has been considered as an other important parameter for testing the performances of proposed system. We assume to have an observation vector collecting S_j observations after that we have selected the same size j n_j times. Each size selection is assumed as a Bernoulli distribution with parametric μ_j characterizing the parametric likelihood function for S_j as:

$$p_j(S_j|\mu_j) = {\mu_j}^{t_j}(1-\mu_j)^{n_j-t_j}, \tag{1}$$

where t_j is the number of times the best choice in terms of preamble size j has been done. We assume (without loss of generality) that the parameter μ_j is characterized with a Beta distribution as the prior for the distribution. This choice is motivated by the fact that Beta distribution is conjugate prior for the likelihood function in Equation (1). Based on Bayes rule we obtain:

$$p_j(\mu_j|S_j) = \frac{p_j(S_j|\mu_j)\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}\mu_j{}^{\alpha-1}(1-\mu_j)^{\beta-1}}{p_j(S_j)}, \quad (2)$$

where,

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1}e^{-x}dx \quad (3)$$

and α and β are the shape parameters of the Beta distribution; we assume (as it is in real world), that we do not have prior information on μ_j and then initial values for $\alpha = \beta = 1$ which yields uniform distribution. Substituting (1) in (2) yields,

$$p_j(\mu_j|S_j) = \frac{\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}}{p_j(S_j)}\mu_j{}^{t_j+\alpha-1}(1-\mu_j)^{n_j-t_j+\beta-1}. \quad (4)$$

$\alpha' = t_j + \alpha$ and $\beta' = n_j - t_j + \beta$ can re-write (4) as:

$$p_j(\mu_j|S_j) = C\mu_j{}^{\alpha'-1}(1-\mu_j)^{\beta'-1} \quad (5)$$

Substituting the normalizing factor C we obtain,

$$p_j(\mu_j|S_j) = \frac{\Gamma(\alpha'+\beta')}{\Gamma(\alpha')\Gamma(\beta')}\mu_j{}^{\alpha'-1}(1-\mu_j)^{\beta'-1}, \quad (6)$$

which is the beta distribution with parameters α' and β',

$$p_j(\mu_j|S_j) = beta(\alpha', \beta'). \quad (7)$$

Thompson sampling preamble length selection algorithm is described in Algorithm 1.

3 Evaluation Results

We have performed a set of measurements of Bit Error Ratio (Fig. 1) and carrier variance (Fig. 2) in a same environments with different light conditions: closed windows and artificial lights turned off in the first scenario, open windows and lamps turned on in the second one, with a fixed distance of 2.5 meters between transmitter and receiver.

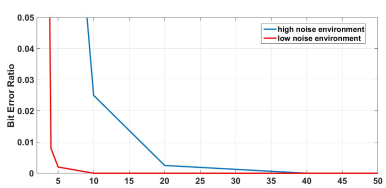

Figure 1. BER for different values of preamble length.

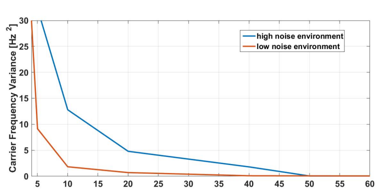

Figure 2. Variance of recovered central carriers for different values of preamble length.

Experimental results show how, in order to achieve an effective reduction of both BER and detected central carrier variation, the optimal value of the preamble length significantly changes when light conditions change. Our adaptive approach dynamically sets the shortest synchronization frame in the two scenarios, that corresponds to ~ 10 in the case of low-noisy environment and ~ 35 in the case of higher noise. This confirms the effectiveness of an adaptive approach in order to dynamically considering short synchronization frames in low noise conditions and increase it if the scenario changes. Statistics on preamble selections in a changeable environment and a comparison between our approach and fixed preambles will be provided in a foreseeable extension of this work.

Algorithm 1 Thompson Sampling

Parameters: J: total number of preamble lengths
j: index of the current preamble length
n: total number of transmitted frames
s_j: current state of the preamble length j
BER_j: current BER of the preamble length j
BER_{th}: BER threshold
t_j: number of successful transmissions so far
$\overline{x}_j$: empirical mean of the overall j states,
α and β: *a priori* (*beta* distribution) model parameter
α' and β': *a posteriori* (*beta* distribution) model parameter
SEND FEEDBACK(): Communicate new preamble length

Initialization: $minBERfound$ = FALSE;
for all j **do** $s_j = 0$;
end for
for all j **do**
  if $BER_j < BER_{th}$ and !$minBERfound$ **then**
    $s_j = 1$;$min_BERfound$= TRUE;
  end if
  update t_j, n_j, α'_j and β'_j
end for

while True **do**
  for all j **do**
    sample $p_j \sim beta(\alpha'_j, \beta'_j)$
  end for
  $m = \arg\max\{\overline{p}_j\}$
  if $BER_m < BER_{th}$ **then**
    $s_m = 1$
  else
    $s_m = 0$
    SEND FEEDBACK()
  end if
  update t_j, n_j, α'_j and β'_j
end while

4 Acknowledgements

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5 References

[1] S. Dimitrov and H. Haas. *Principles of LED Light Communications: Towards Networked Li-Fi*. Cambridge University Press, 2015.

[2] M. Heydariaan, S. Yin, O. Gnawali, D. Puccinelli, and D. Giustiniano. Embedded visible light communication: Link measurements and interpretation. In *EWSN*, pages 341–346. Graz, February 2016.

[3] A. Maskooki, V. Toldov, L. Clavier, V. Loscri, and N. Mitton. Competition: Channel exploration/exploitation based on a thompson sampling approach in a radio cognitive environment. In *EWSN*. Graz, February 2016.