Algorithme de récupération de porteuse pour des systèmes de communication de lumière visible adaptées au contexte

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La communication par lumière visible (VLC) suscite beaucoup d'intérêt à la fois dans la communauté scientifique et industrielle. En dépit de cet intérêt croissant, VLC en est encore à ses balbutiements et il a été réalisé que les techniques de communication de contrôle physique et d'accès au support (MAC) bien évaluées dans les contextes de communication traditionnels (sans fil) ne peuvent pas être appliquées dans le domaine VLC. En effet, les interférences externes sont de nature et d'impact différents. Les lumières artificielles et la lumière du soleil peuvent perturber la communication et nous avons observé que les conditions extérieures changent de manière imprévisible et abrupte. Sur la base de ces considérations, il a été réalisé que les émetteurs et les récepteurs doivent être équipés d'une sorte d'intelligence les rendant capables de réagir dynamiquement aux changements externes afin de rendre le système de communication plus robuste. Dans ce travail, nous avons étudié l'impact de la longueur du préambule afin de réaliser un mécanisme de récupération de porteuse efficace entre un émetteur et un récepteur. Nous avons remarqué que différentes conditions externes nécessitent des longueurs de préambule différentes afin de réaliser une récupération de porteuse efficace avec un faible impact en termes de taux d'erreur de morsure (BER). Nous avons étudié les différentes conditions externes et leur impact sur le système de communication et nous avons proposé une formulation de bandit multi-bras de la définition de la longueur du préambule basée sur l'approche d'échantillonnage de Thompson. Cette logique d'intelligence artificielle a été implémentée côté récepteur et une preuve de concept a été implémentée afin de valider l'approche dans un environnement réel avec de réels changements externes. Les résultats montrent que l'approche d'échantillonnage de Thompson est très réactive aux conditions externes.

Mots-clefs : Communication Lumière Visible, Récupération du Porteur, Échantillonnage Thompson, Bandit Multi-armé, Intelligence Artificielle

1 Introduction

Recently, Visible Light Communication systems [1] [2] have gained a lot of attention, however, one of the most difficult limitation to overcome for a wide diffusion of this technology is represented by the significant effects of sunlight and other external optical sources on communication performances. 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 which is implemented by appending a preamble (repetitive insertion of sequences), to the transmitted data. At the receiver, a clean copy of the appended message is correlated with the received symbol stream for frame alignment. The size N (number of bits) of the preamble impacts on the performance of the communication system. Indeed, 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, especially in the case of noisy environmental conditions. Different external environmental conditions need different values of preamble length.

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]. 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 transmitting stage, a photodiode, a trans-impedance amplifier and a second Arduino board at the receiving stage. Transmitted signal is directly generated through software and signal processing at the receiver side is carried out by programming a virtual instrument using the commercial software LabView. Experimental results have shown 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.

2 System and Algorithm Description

A Multi-arm bandit formulation is frequently applied when a fixed limited set of resources must be allocated between competing choices in a way that maximizes an expected payoff, using an exploration-exploitation mechanism. In our case, in order to properly set the correct preamble length, the system acquires new knowledge on the environment through Bit Error Rate measurements after each received frame (exploration), and takes its decision, namely the preamble length set, according to current knowledge (exploitation). In particular, an agent tries to achieve as much award as possible by playing the most rewarding arm among J arms (J in our case represents the possible choices of the size N, that could be potentially unlimited but not all the sizes are meaningful, so we consider 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. This choice is motivated by the fact that at the receiver side all the data needed to implement the algorithm are known. 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. We introduce the agent A representing 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 (that in our case is representing the size of preamble) has played after n steps and μ_j to be expected reward of j^{th} arm. In practice, the preamble size N is found in average $\mu_j n_j$ times in n_j measurements. In order to directly minimize errors due to a variation of the recovered carrier, without considering other phenomena, the criterion trigger we apply in this case 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 :

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

where,

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

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

In a real indoor scenario, disturbing light sources are mainly represented by sunlight penetrating by windows and external artificial lights illuminating the scenario but not included in the VLC system. For this motivation, a set of measurements of Bit Error Ratio (Fig. 1) and carrier variance (Fig. 2) in a same environments with different light conditions have been performed. Specifically, we have considered closed windows and artificial lights turned off in the first scenario, open windows and artificial lamps turned on in the second one with a fixed distance of 2.5 meters between transmitter and receiver. Experimental results

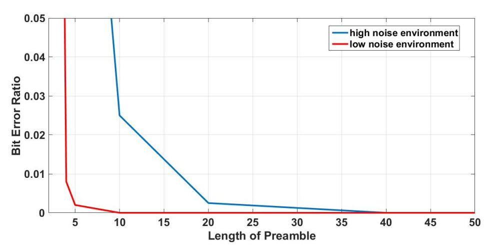

FIGURE 1: BER for different values of preamble length.

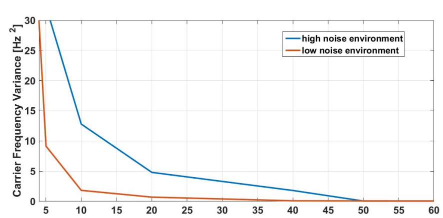

FIGURE 2: Variance of recovered central carriers for different values of preamble length.

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 (reducing consequentially the overall overhead) in low noise conditions and increase the length of control frame in the case the scenario changes.

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
$\bar{x}_j$: 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_BER_found= 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

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