USING RFID TECHNOLOGY TO INTRODUCE PROPERTIES OF LMS

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ABSTRACT

This paper presents a new course design to enhance students' interest in our graduate curriculum of morden digital signal processing (MDSP). The familiar radio frequency identification (RFID) technology is introduced to reveal the fundamentals of the least-mean-square (LMS) algorithm. Students are encouraged to encode their customised data into their respective RFID tags, and to use the software-defined radio (SDR) platform to monitor the inventory process integrated within RFID communication systems. After acquiring the digital signal from the SDR hardware, they need to perform adaptive channel estimation and signal detection to identify the customised data. By applying appropriate mathematical tools in the Matlab programming environment to solve the signal detection problem in two different communication scenarios, students reported to have had a deeper understanding of the signal processing concepts of adaptive filtering techniques in a self-directed manner.

Index Terms— least-mean-square (LMS), radio frequency identification (RFID), adaptive filters, signal processing education

1. INTRODUCTION

Adaptive filtering technique has found unprecedented practical applications since it was first introduced in 1960 [1]. As a result, it has been included in the syllabus of modern digital signal processing (MDSP) - one of our graduate courses for students majoring in Information and Communication Engineering at Southeast University, Nanjing, China. The least-mean-square (LMS) [2,3], which adapts the coefficients of an FIR filter in order to minimise the mean-square error (MSE) between its output and the desired signal, is the most widely used adaptive filtering algorithm. A solid understanding of the performance and limitations of adaptive filters is difficult without an integrated knowledge of the mechanism and properties of LMS. To that end, many didactic strategies have been demonstrated to improve students' comprehensibility on LMS [4, 5]. For instance, LMS was introduced to solve the dynamic weighting problem in the application of fruit-sorting and -grading in fruit-packing houses in [5].

Traditionally in Southeast University, the mathematical concepts of adaptive filters were taught in lectures only. In order to educate the next generation of DSP engineers, similar to [5,6], we believe that hands-on engineering experiences of real-world applications are indispensable for students to design and analyse adaptive filters in practical DSP problems [7]. In our recent work [8], we brought radio frequency identification (RFID) technique [9] into a participatory coursework of the digital communication curriculum, and have won plenty of praise from undergraduate students in our university. In the past few years, RFID has been successfully applied in many of different areas like logistics and asset tracking, which have already provoked certain intellectual curiosity among students. Its simple medium access control (MAC) layer also enables a quick experimental set-up for students. Therefore, RFID is a desired vehicle to convey hands-on participation and intellectual stimulation to students.

Within this learning framework, we present a new course design which uses the RFID technology to elucidate properties of LMS. First, the students need to encode their customised data into their respective RFID tags, and monitor the inventory process within the RFID system on a software-defined radio (SDR) platform [10]. After that, they are required to apply the LMS algorithm to adaptively equalise the received digital signal, and decode to identify the customised data. During the experiment, they need to complete two assignments which are tailored to manifest the mechanism and properties of LMS. With this participatory approach, students are able to solidify the theoretical knowledge taught in the MDSP curriculum in a more engaging way, and explore additional concepts partially covered during the lectures.

2. NEW COURSE DESIGN

This section explains the reason for RFID becoming our choice as the experimental framework and shows how to involve RFID in this coursework. Two assignments built on the RFID system are presented, which are designed to encourage students to understand the properties of LMS in a self-directed way.

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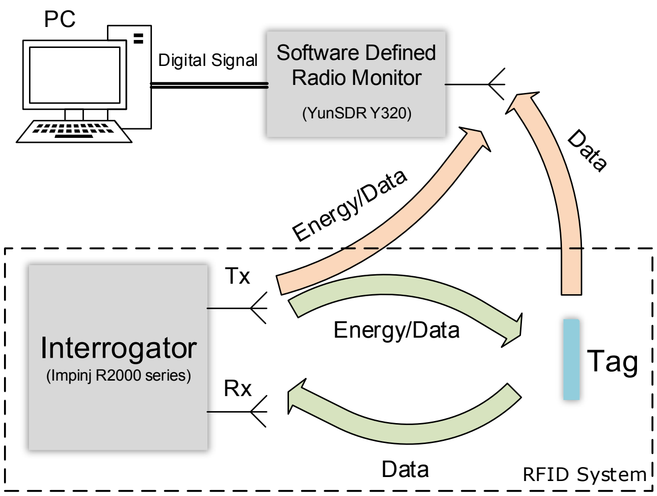

Fig. 1. Block diagram of the coursework set-up

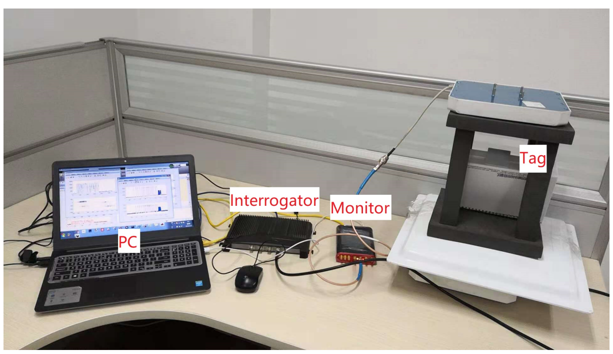

Fig. 2. Experimental set-up of this coursework.

2.1. Set-up of the RFID coursework

RFID tags come in a broad range of shapes and sizes, depending on the required read range in a different physical environment. The passive tag does not require on-board power to supply the tag response and has a read range of more than 10 metres. Consequently, it becomes a popular choice in ultra-high-frequency (UHF) range applications like logistics and automatic toll collection. The ISO 18000-6C standard [9] has specified the physical and logic requirements for an RFID system operating in the UHF band of 860 MHz - 960 MHz. The UHF RFID system used in our coursework is shown in Fig. 1, which consists of an *Impinj R2000* RFID interrogator and an ISO 18000-6C passive tag. The SDR monitor alongside the RFID system is used to listen and record the signals sent and received within the tag and the interrogator. The monitor is wired to a personal computer (PC), which is used by students to analyse the digitalised signal in the Matlab programming environment. The real-world experimental set-up of this coursework is shown in Fig. 2.

The communication flow between the interrogator and the

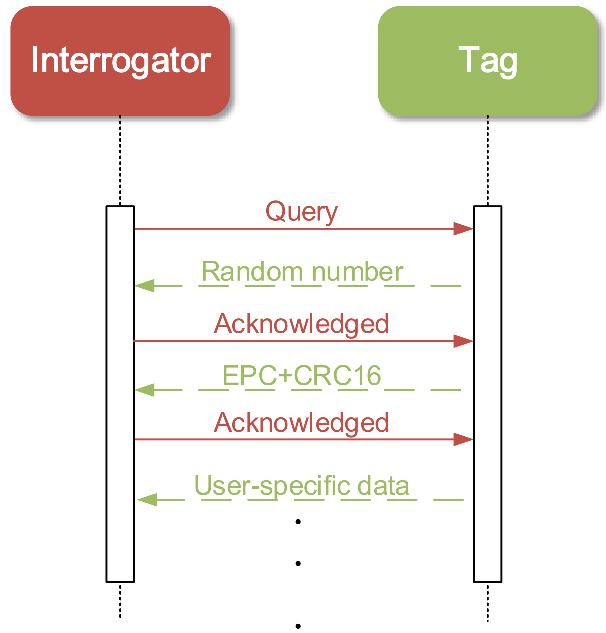

Fig. 3. The inventory round of an 18000-6C RFID system, where EPC and CRC stand for electronic product code and cyclic redundancy check respectively.

tag, i.e., the inventory round, is explained in Fig. 3. At the beginning, the interrogator sends a query command to activate the passive tag. The tag shall encode the backscattered data via a specific modulating scheme, such as the Miller modulation. After receiving twice acknowledgements from the interrogator, the tag responds with the user-specific data which are customised by students themselves and stored in the tag memory. The participations between the interrogator and the tag in each inventory round is managed via a state machine which comprises of only seven tag states. This easy-to-understand MAC layer of the ISO 18000-6C standard facilitates a plain experimental set-up for students and helps to bring them into practical problems in a rapid manner.

The flowchart of this participatory coursework design is given in Fig. 4, including all the tasks before and during the experiment. In the preparation, a 18000-6C tag is given to all students. They are required to customise their own data and write them into the user memory of their respective tags. During the experiment task, they need to set up an appropriate sampling rate on the monitor before it can start to record the inventory round within the RFID system. The indicator light on the interrogator will turn on once the inventory round is finished, and each student needs to load the recorded signal into a PC. After that, students are asked to perform adaptive channel equalisation and signal detection based on the LMS and its variants, in order to compare the decoded data with their customised ones.

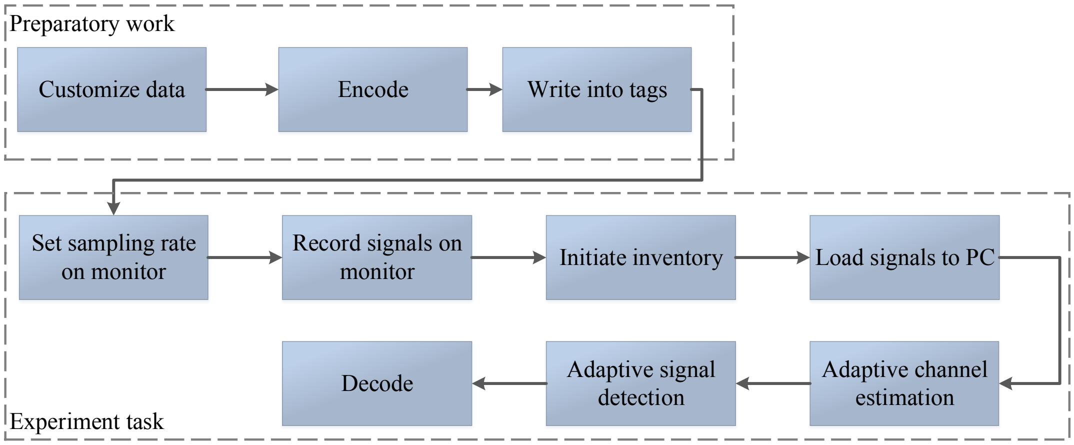

Fig. 4. Flowchart of the experiment.

2.2. Description of the problem

In the RFID system, the interrogator provides the power supply to the tag in the form of a continuous sinusoidal carrier wave. As a response, the tag backscatters its information to the interrogator via the switch of its antenna input impedance to the reflect state. Given a flat fading channel between the monitor and the tag, the backscattered signal recorded at the monitor $s(t)$ can be expressed as

$$s(t) = a(t)h\Delta_\sigma \sin(\omega_c t + \phi) \quad (1)$$

where $a(t)$ is the pulse-amplitude-modulated tag-to-interrogate data, h is the channel coefficient, Δ_σ is the backscattering modulation efficiency, ω_c is the operating frequency and ϕ is the phase shift. The RF signal, $s(t)$, is downconverted to the baseband and digitised at a sampling rate of f_s. The baseband discrete signal arrived at the monitor $s(n)$ can be represented as

$$s(n) = ga(n) + v(n) \quad (2)$$

where $g = h\Delta_\sigma e^{j\phi}$ is the mixed coefficient of channel, backscattering efficiency and phase shift, $v(n)$ is the observation noise. In ISO 18000-6C, the tag-to-interrogate data $a(n)$ contains a preamble $a_p(n)$ in front of the user-specific data $a_u(n)$. In order to successfully resolve $a_u(n)$ from the digitised signal, students are suggested to perform the channel equalisation initially based on the provided preamble, $a_p(n)$. This is often achieved by minimising the mean-square-error between the observed $s(n)$ and the estimated $\hat{s}(n)$, given by

$$J(n) = E[|s(n) - \hat{s}(n)|^2] = E[|s(n) - \hat{g}(n)a_p(n)|^2] \quad (3)$$

The most popular LMS adaptive algorithm is then applied to solve this problem. The next section shows two student assignments, designed to reveal the properties of LMS in this particular problem.

2.3. Assignments to introduce the properties of LMS

2.3.1. Assignment 1: Understanding the stochastic-gradient property of LMS

Students were taught that the optimal iterative solution to an unconstrained optimisation problem like (3) is the steepest-descent algorithm [3], in which the update of $\hat{g}(n)$ is derived as

$$\begin{aligned}\hat{g}(n+1) &= \hat{g}(n) - \mu\frac{\partial J(n)}{\partial \hat{g}^*(n)} \\ &= \hat{g}(n) + \mu\Big(E[s(n)x^*(n)] - E[|x(n)|^2]\hat{g}(n)\Big) \quad (4)\end{aligned}$$

This shows that in the sense of steepest descent, the update direction of $\hat{g}(n)$ is chosen to point in the opposite direction of the conjugate gradient of $J(n)$. The basic idea of LMS is to replace the statistics in (4) with an instantaneous approximation [11], to give

$$\begin{aligned}\hat{g}(n+1) &= \hat{g}(n) + \mu\Big(s(n)x^*(n) - |x(n)|^2\hat{g}(n)\Big) \\ &= \hat{g}(n) + \mu e(n)a_p(n) \quad (5)\end{aligned}$$

where $e(n) = s(n) - \hat{g}(n)a_p(n)$ is the estimation error. Rather than teaching this stochastic-gradient nature of LMS as an abstract notion [12], we visualise its characteristics in a real-world RFID channel equalisation case. This is achieved by imitating the statistical information of the steepest-descent algorithm in (4) with extra temporal samples provided by the oversampling technique [13, 14]. At a higher sampling rate, there will be more iterative updates on the channel estimator $\hat{g}(n)$ within the same time slot, so that a better equalisation can be expected based on the user-specific data. In this assignment, students need to set a group of different oversampling factors on the SDR monitor, to verify this stochastic-gradient property of LMS. Fig. 5 illustrates the constellation of the original user-specific data, and the data

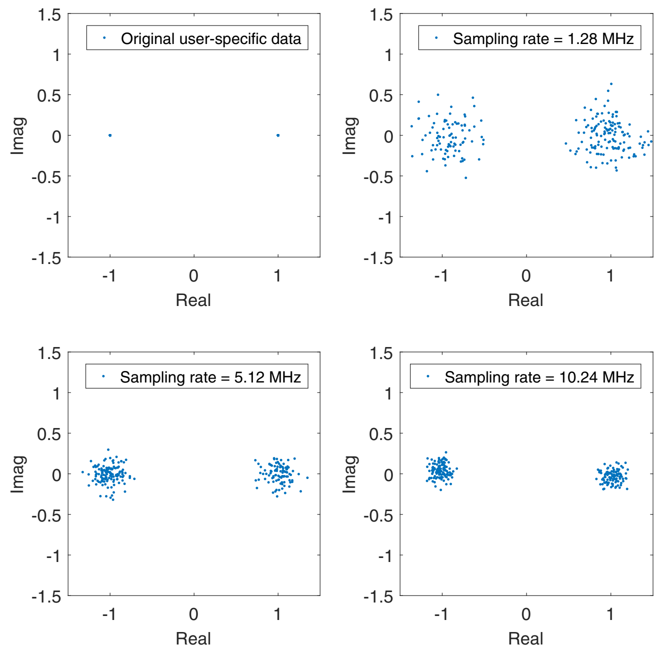

Fig. 5. Constellations of the user-specific data after adaptive channel equalisation at different sampling rates.

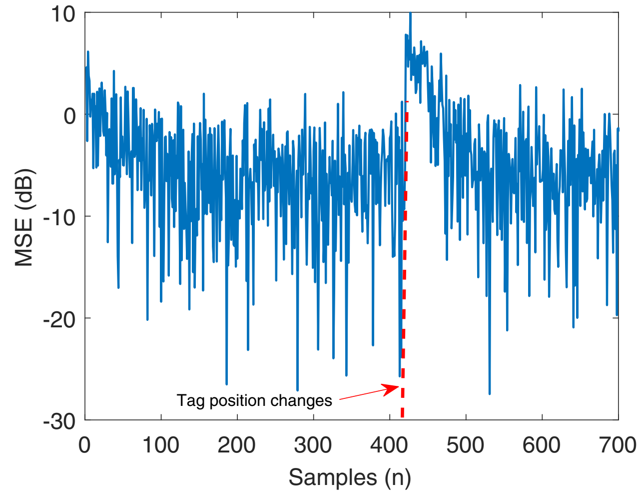

Fig. 6. Convergence performance of the mean-square-error $J(n)$ of the LMS after tag position changes during the channel equalisation.

after the adaptive channel equalisation at different sampling rates, i.e., 1.28 MHz, 5.12 MHz and 10.24 MHz. Since the required sampling period of $a(t)$ in 18000-6C is 6.25 μs, these sampling rates correspond to an oversampling factor of 8, 32 and 64, respectively. In this way, from Fig. 5 students become aware that the best equalised user-specific data are those that digitised at the highest sampling rate.

2.3.2. *Assignment 2: A comparison to the block-based least squares (LS) method*

Compared with block-based methods like least-squares (LS), the LMS has the advantages of a lower computational complexity and faster adaptation for potentially time-varying channels. In this assignment, students first need to compare the elapsed time of both the LS and LMS channel equalisation, measured by the stopwatch timer function *tic* and *toc* in the Matlab environment [15]. Next, in order to show that LMS better copes with changes in the experiment environment, the tag is moved from its original position during each inventory round. Students are required to analyse the digitised signal to manifest the tracking ability of the LMS. This is achieved by showing the convergence performance of the mean-square-error $J(n)$ during the channel equalisation process. As shown in Fig. 6, students experience the LMS can re-converge to the steady state after the tag position changes.

3. ASSESSMENTS

MDSP is a mandatory curriculum offered to graduate students in Southeast University, Nanjing, China. Through our initiative that students can train themselves with the ability to solve difficult engineering problems via learning advanced signal processing skills like the participatory way in [6, 8], we have incorporated this coursework into the curriculum since the Fall term of 2017. From then on, 23 students have undertaken this coursework. Although it is not a large number, some positive feedback has already been received. So far, the completion rate of the Assignment 1 and 2 are respectively 86.9 % and 95.7 %. This is a satisfactory result and has proved that the difficulty level of this coursework was well within their reach. 20 of of 23 students felt that the added coursework engaged their engineering interests and helped them understand the key concepts of the curriculum. Furthermore, 3 students suggested to us to design more similar coursework within the MDSP curriculum to give a more systematic learning experience.

4. CONCLUSION

An practically relevant way to support the modern digital signal processing (MDSP) curriculum has been introduced. Students were required to apply the LMS algorithm to perform adaptive channel equalisation and signal detection to identify the customised user-specific data on the tag in a 18000-6C RFID system. Two assignments have been designed to reveal the fundamental properties of LMS. With this participatory approach, students have become aware of the significance of LMS with respect to technological advancements they are familiar with, and to appreciate the social impact of the MDSP curriculum as well.

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