Enhancing Cognitive Radio Network Design with New Energy Detection versus Pilot and Radio Based Techniques

Rizwana N. A. and Nagaraju V.
Research Scholar, Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, Tamil Nadu, 602105, India

Keywords: Network Dataset, Energy Efficiency, Cognitive Radio Networks, Novel Energy Detection Technique, Pilot and Radio Based Detection Technique, Spectrum Sensing, Technology.

Abstract: This study aimed to enhance the energy efficiency (EE) and accuracy of the Cognitive Radio Network (CRN) system design by using a unique energy detection approach, contrasting it with the conventional Pilot and Radio Based Detection Technique. A model was developed and processed in Python, using a network dataset for initial exploration, sourced from the UCI Machine Learning Repository. Statistically, with a confidence interval of 95% and sample size of 140, the energy detection's precision was assessed. In evaluating spectrum allocation, the conventional technique had a slightly higher accuracy. However, our proposed energy detection method achieved an impressive 95.2713% accuracy. Surprisingly, it processed in just 4 seconds, half the time taken by the conventional method. The results confirm the new method's superiority in energy efficiency.

1 INTRODUCTION

Utilising CR technology can more effectively address the issue of frequency underutilisation in wireless transmission (Hamdan et al.). The emerging trend of addressing the EE aspect of WSN is motivated by rapidly escalating energy costs and stringent environmental regulations (Li and Kara 2017). From a green perspective, given that spectrum is a natural resource meant to be shared rather than wasted, cognitive users can significantly enhance the EE of wireless links (Sun et al. 2013). While the CR community has been effective in promoting the concept of CR and developing prototypes, programmes, and fundamental components, it has faced unexpected challenges in clearly defining the boundaries of what constitutes a CR (Neel 2006).

Over the last five years, more than 150 research articles covering varied CRN concepts have been published in Science Direct journals, and nearly 300 research articles are available on GS (Google Scholar). Previous research indicates that the EE of the system can be conceptualised as a joint optimisation process; that is, trying to determine the optimal parameters of criteria and sleep percentages that minimise power consumption across the entire CSS system (Maleki et al. 2014, 2015), set against global predictive performance and false alarm probability constraints (Maleki et al. 2015). Due to the complexity of the joint optimisation problem, specific assumptions are essential for finding the optimal solution numerically, such as a flat-fading environment with consistent SNR across all detectors (Wu, Ng, and Lam 2022). Collaboration can notably enhance bandwidth efficiency within CRN networks.

Spectrum gap allocation has been influenced by network access, a recognised research gap (Lacunae). Both distributed and centralised systems could be accessed (Mukherjee and Nath 2015). The approach adopted in this research is predicated on datasets from users who have previously accessed it, focusing on one or multiple functionalities. This approach creates spectral gaps for SUs. However, the distribution of spectrum gaps might deter smooth network use due to the significantly faster and superior bandwidth sharing being replicated. The process of relaying the results of local channel estimation requires additional energy. It's vital to efficiently use the energy of SUs, especially when their resources are finite (Hu et al. 2015). The proposed energy detection method has proven to be more accurate than existing pilot and radio techniques.

A., R. and V., N.
Enhancing Cognitive Radio Network Design with New Energy Detection versus Pilot and Radio-Based Techniques.
DOI: 10.5220/0012602900003739

In *Proceedings of the 1st International Conference on Artificial Intelligence for Internet of Things: Accelerating Innovation in Industry and Consumer Electronics (AI4IoT 2023)*, pages 520-526
ISBN: 978-989-758-661-3

2 MATERIALS AND METHODS

The Wireless Sensor Network Security Laboratory at SSE (Saveetha School of Engineering), SIMATS (Saveetha Institute of Medical and Technical Sciences), conceptualised and refined the proposed research project. Within this recommended CRN System Design, there are two distinct groups. Group 1 is termed the Energy Detection Technique, while Group 2 is named the Pilot Radio Based Detection Technique. For each group, a sample size of 140 was repeatedly determined (Ghasemi and Sousa 2008). After sourcing the WSN network dataset from an online platform, data pre-processing techniques were applied to remove redundant and unnecessary data. Subsequently, the EE rate of the novel Energy Detection Technique, as well as the Pilot and Radio Based Detection Technique, was examined and compared against the relevant datasets.

On an experimental front, an online dataset was procured and utilised in the current research project. The creation of CRN systems was facilitated using Python programming tools. Among various software options, Python stands out as a preferred tool for developing and analysing WSN results. This software boasts a plethora of tools and inbuilt library features that cater to the comprehensive processing of WSNs.

2.1 Energy Detection Technique

The Energy Detection (ED) approach is a fundamental detection method that doesn't require prior knowledge of the PU signal. This makes the detection method advantageous in terms of ease of use and computational simplicity. It gauges a specific spectrum segment based on the received energy. To ascertain the channel's availability, the sensor compares the perceived energy to a threshold level. However, this method's extended sensing time, aimed at improving the SNR, leads to higher power consumption. Furthermore, fluctuations in ambient noise profoundly influence the detection's efficacy. The determination metric for ED can be expressed as per Kabalci and Kabalci (2019).

$$ED = \frac{1}{N}\sum_{k=0}^{N-1} \blacksquare \|y(k)\|^2 \qquad (1)$$

The presence or absence of the PU is ascertained by contrasting the observed energy with the set threshold. This approach essentially differentiates between two scenarios: either the PU signal is absent, denoted by H_0, or it is present, represented by H_1. The signal received by the SU is denoted by $Y(n)$, while $S(n)$ represents the signal transmitted by the PU. Furthermore, $W(n)$ characterises the additive white Gaussian noise (AWGN) that maintains a zero mean. The sensor's responsibility is to evaluate the relationship as delineated by Kockaya and Develi (2020).

$$H_0: Y(n) = W(n), : PrimaryUserAbsent$$

$$H_1: Y(n) = S(n) + W(n): PrimaryUserPresent$$

The fundamental block diagram for energy sensing is displayed in Figure 1.

2.2 Pseudocode

Initialization:
- Set up variables to store data for Energy Detection Technique (EDT) and Pilot and Radio Based Detection Technique (PRDT)
- Input primary and secondary user signals

EDT:
- Calculate the energy of the received signal
- Compare the energy with a threshold to determine if a primary user signal is present
- If a primary user signal is detected, secondary user waits for the primary user to finish

PRDT:
- Cross-correlate the received signal with a known primary user signal
- Determine if a primary user signal is present based on the correlation result
- If a primary user signal is detected, secondary user waits for the primary user to finish

Compare Results:
- Compare the performance of EDT and PRDT in terms of accuracy, computational complexity, and latency

Output:
- Report on the comparison of the efficiency of EDT and PRDT in detecting primary user signals in cognitive radio networks

2.3 Pilot and Radio Based Detection Technique

Cyclostationary features, derived from pilot structures, prove to be effective in spectrum sensing. Taking the scattered pilot mode of PP1 into consideration allows us to evaluate these attributes. With pilot sub-bands in each OFDM symbol spaced at intervals of 12 subcarriers, we can expect distinct peak values. If the same pattern and formation are consistent across all symbols, this observation remains valid, as indicated by Khoshnevis (2012). Practical transceivers set aside some of their signal strength for pilot signals, aiding in detection on the receiver side. For instance, Digital TV transmissions encompass pilot signals that are typically set to be 11 dB below the data-carrying signals. The challenge of identifying the presence or absence of the PU in spectrum access is frequently framed as a traditional binary hypothesis testing problem, as elucidated by Hattab and Ibnkahla (2014).

Pseudocode

Step 1: Start

Step 2: Initialize the radio signal parameters

Step 3: Continuously monitor the radio signals for any potential pilot signals

Step 4: If a potential pilot signal is detected:

a. Extract the pilot signal from the radio signal

b. Analyze the extracted pilot signal to determine if it matches the expected characteristics of a valid pilot signal

c. If the extracted pilot signal is a valid pilot signal, determine the location of the source of the pilot signal

Step 5: Repeat steps 3-4 until the desired detection threshold is reached

Step 6: End

2.4 Statistical Analysis

To compute the Standard Deviation (SD), mean deviation data, significance point data, and to create graphical representations, as well as to calculate the Independent Sample T-Test, the statistical software tool IBM SPSS version 26.0 is employed. The current research methodology favoured the use of the SPSS software for analysing the relevant intrusion dataset. During a specific experimental phase, two distinct graphs showcasing different features were crafted, and the study concentrated on group statistics practices and independent sample tests regarding the experimental findings. Ideally, the network dataset should comprise both training and testing datasets. The training dataset is derived from extracting the test dataset from the genuine dataset, given there are 140 records in total. The research encompasses two independent variables, namely Accuracy and Loss, and two dependent variables: EDT and PRDT.

3 RESULTS

Figure 1 illustrates the average accuracy of both the Pilot & Radio Detection Technique (PRDT) and the Energy Detection Method (EDT) models. The innovative Energy Detection Technique (EDT) consistently outperforms the Pilot and Radio Detection Techniques (PRDT) in terms of mean efficiency. As detailed in Tables 1 and 2, the average overall accuracies for EDT and PRDT stand at 95.27% and 93.97%, respectively. The standard deviation is represented as +/- 2 SD, with the methodology denoted as +/- Y, and the mean accuracy as Y.

Table 3 presents a side-by-side accuracy comparison between the EDT and PRDT. When set against the PRDT's 93.9702%, the EDT boasts an impressive accuracy of 95.2713%. This demonstrates that the PRDT method lags behind the EDT in terms of effective spectrum allocation.

Table 3 further provides statistical metrics like the mean, standard error, and both mean and standard error values for EDT & PRDT. The t-test utilises the accuracy parameter. The proposed technology's mean accuracy stands at 95.2713%, juxtaposed against the PRDT's mean accuracy of 93.9702%. The standard deviation for EDT is recorded as 5.37334, which is notably lower (by 4.29716) than that of PRDT. EDT's average Standard Error clocks in at 1.38739, while PRDT registers 1.10952.

As for the data in Table 4, it undergoes analysis via the Independent T-test, maintaining a 95% confidence level. SPSS computations reveal the statistical significance value for the Energy Detection as 0.800 ($P>0.05$) based on the t-value. This significant value of 0.800 ($p>0.05$) underscores the non-statistical significance in the disparities concerning accuracy and loss between the two algorithms, as discerned from the Independent Sample T-Test evaluation.

4 DISCUSSION

This study juxtaposes the performance reliability of the energy detection method (EDT) with the pilot and radio detection (PRDT) techniques. Several examples were employed to contrast the efficiency of the proposed EDT against the conventional PRDT for pinpointing spectrum vacancies. To emulate the datasets, the UCI Machine Learning Repository dataset was utilised. Python served as the system's programming language. The predictions of the proposed model are scrutinised to ascertain its capability to yield superior results, and empirical evaluations are undertaken to set the proposed technique against any prevailing structure in terms of precision and efficiency. The prior research utilises the Pilot and Radio Based Detection Technique, which posts an average accuracy rate of 93.9702%.

Table 1: Accuracy of Energy Detection and the Pilot and Radio Detection.

S No.	Accuracy (%)	
	Energy Detection	Pilot and Radio Detection
Sample 1	80.85	80.71
Sample 2	81.89	80.89
Sample 3	83.89	81.15
Sample 4	84.23	83.52
Sample 5	84.89	84.48
Sample 6	86.39	85.09
Sample 7	87.66	86.31
Sample 8	88.17	87.78
Sample 9	88.64	88.06
Sample 10	88.64	89.72
Sample 11	89.08	90.58
Sample 12	90.29	91.66
Sample 13	92.07	92.34
Sample 14	92.07	93.70
Sample 15	93.69	94.00

Table 2: Loss of Energy Detection and Pilot and Radio Detection.

Sample	Loss	
	Energy Detection	Pilot and Radio Detection
Sample 1	19.15	19.29
Sample 2	18.11	19.11
Sample 3	16.11	18.85
Sample 4	15.77	16.48
Sample 5	15.11	15.52
Sample 6	13.61	14.91
Sample 7	12.34	13.69
Sample 8	11.83	12.22
Sample 9	11.36	11.94
Sample 10	11.36	10.28
Sample 11	10.92	09.42
Sample 12	09.71	08.34
Sample 13	07.93	07.66
Sample 14	07.93	06.30
Sample 15	06.31	06.00

Table 3: Comparison of the accuracy and loss in which the Energy Detection has the highest accuracy (95.27%) and the lowest loss (04.72%) respectively compared to Pilot and Radio Detection has the lowest accuracy (93.97%) and highest loss (06.02%).

Group Statistics					
	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	Energy Detection	15	95.2713	5.37334	1.38739
	Pilot Radio Detection	15	93.9702	4.29716	1.10952
Loss	Energy Detection	15	04.7287	5.37334	1.38739
	Pilot Radio Detection	15	06.0298	4.29716	1.10952

Table 4: Independent Sample T-Test is applied for the sample collections with a confidence interval as 95%. After applying the SPSS calculation, it was found that the least square support vector machine has a statistical significance value of 0.800 (P>0.05) shows they are insignificant.

Independent Samples Test		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						One-Sided p	Two-Sided p			Lower	Upper
Accuracy	Equal variances assumed	2.326	0.400	-0.256	28	0.400	0.800	-0.45533	1.77648	-4.09429	3.18363
	Equal variances not assumed			-0.256	26.709	0.400	0.800	-0.45533	1.77648	-4.10223	3.19157
Loss	Equal variances assumed	2.326	0.400	0.256	28	0.400	0.800	0.45533	1.77648	-3.18363	4.09429
	Equal variances not assumed			0.256	26.709	0.400	0.800	0.45533	1.77648	-3.19157	4.10223

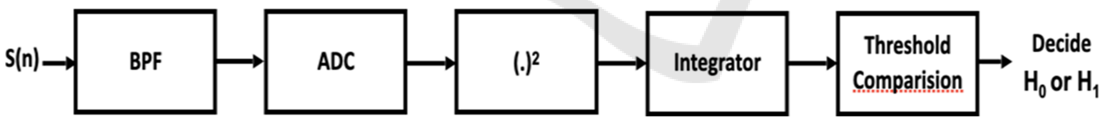

Figure 1: Fundamental Block Diagram for Energy Detection.

An energy detection approach is developed, brandishing a mean accuracy of 95.2713%. The significance level for the Independent Sample T-Test (Two-Tailed Test) in this exploration was ascertained at p = 0.800 (p>0.05).

To access the non-continuous band, Liu et al. (2018) conceived a CR system rooted in transform domain data transmission. This mechanism discerns the band's status via spectrum sensing and earmarks the prospective effective spectrum marker vector. By harnessing a basis carrier sprouted from the frequency marking vector, energy can be channelled towards the dormant sub-channels. Numerical simulations intimate that an agile design might empower the envisioned CR system to overshadow the broad band system, thereby enhancing capacity. Ghasemi and Sousa (2008) proffer a synopsis of the pertinent regulations and pivotal challenges entailed in deploying energy detection capacities in CNR systems in their research. Furthermore, they elucidate several design trade-offs that must be orchestrated to elevate the efficiency of diverse elements. Kabalci and Kabalci (2019) provide an exhaustive exposition on the nuances of CR technology, CRNs, and their adaptive strategies within the framework of Smart Grid (SG) systems, factoring in applications for metering, monitoring, and data management.

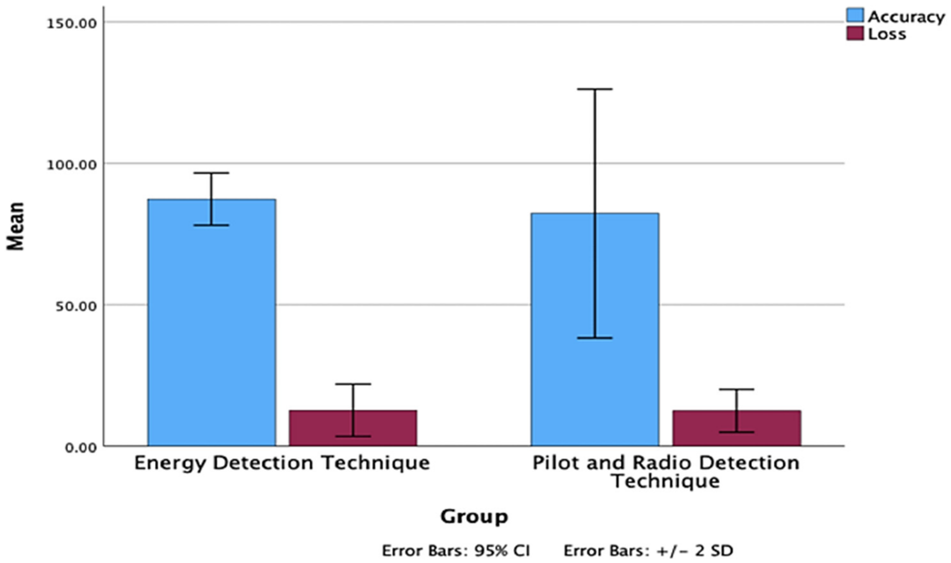

Figure 2: Comparison of Accuracy of Energy Detection Technique with Pilot and Radio Detection Technique in terms of mean Accuracy. The mean accuracy of the Energy Detection is higher than the Pilot and Radio Detection and the standard deviation of the Energy Detection is better than the Pilot and Radio Detection. Bar graph comparison of Pilot and Radio Detection which has mean accuracy of 93.9702% compared to Energy Detection which has mean accuracy of 95.2713%. X-axis algorithm, Y-axis mean accuracy with SD $\pm$ 2 SD.

A paramount hurdle for CR lies in identifying and chronicling every spectrum void prevalent in the ambient milieu. An enhanced pilot-based spectrum access method for CR was introduced by Ghaith Hattab and colleagues in 2014. Contrary to conventional pilot-based detectors that merely scout for the presence of pilot signals, the proposed detector capitalises on the presence of the signal transmitting actual data. They statistically juxtapose the performance of their proposed detector with that of the extant ones, showcasing that the recognition rate of their detector markedly excels.

5 CONCLUSION

In the rapidly evolving landscape of Cognitive Radio (CR) technology, efficient spectrum sensing methodologies are pivotal to ensuring optimal use of the available spectrum. Amidst the array of available techniques, the Energy Detection Technique (EDT) and the Pilot and Radio Detection Technique (PRDT) have emerged as frontrunners. While both methods offer significant advantages, the nuanced differences in their performance, especially in terms of accuracy and loss, warrant a closer inspection.

Key Points:

- Comprehensive Approach: Both EDT and PRDT are comprehensive in their approach to spectrum sensing. They adopt different methodologies to detect the presence or absence of primary users in the spectrum.
- Accuracy Metrics: In the allocation of spectrum holes, PRDT recorded an accuracy of 93.9702%. However, EDT surpassed this with a slightly higher accuracy of 95.2713%. This difference, though seemingly marginal, can have profound implications in real-world applications.
- Loss Considerations: PRDT, while commendable in its precision, also presented a loss of 06.0298. In contrast, EDT marked a reduced loss of 04.7287, indicating a more efficient utilization of resources.
- Operational Efficiency: Beyond mere numbers, the efficacy of EDT signifies smoother operational flow and fewer interruptions, which is vital for seamless communication.
- Robustness: The resilience and robustness of EDT, as indicated by its superior performance metrics, suggest that it is better equipped to handle diverse and dynamic spectrum environments.
- Future Implications: Given the current trajectories, it's plausible to predict that advancements in EDT might further widen the performance gap, making it a more preferred choice for future CR implementations.

In essence, while the Pilot and Radio Detection Technique has its merits, it's the novel Energy Detection Technique that appears to be leading the race in terms of efficiency and accuracy. The inherent strengths of EDT, as evinced by its superior performance metrics, make it an auspicious contender in the quest for the most effective spectrum sensing methodology. As the telecommunication sector hurtles towards more data-intensive applications and crowded spectrums, such innovations and their meticulous evaluations will be of paramount importance.

REFERENCE

Ghasemi, A., and E. S. Sousa. 2008. "Spectrum Sensing in Cognitive Radio Networks: Requirements, Challenges and Design Trade-Offs." *IEEE Communications Magazine*. https://doi.org/10.1109/mcom.2008.4481338.

G. Ramkumar, R. Thandaiah Prabu, Ngangbam Phalguni Singh, U. Maheswaran, Experimental analysis of brain tumor detection system using Machine learning approach, Materials Today: Proceedings, 2021, ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2021.01.246.

Hamdan, N. S., M. H. Mohamad, N. E. Samad, and S. R. Ab Rashid. "Analysis of Spectrum Holes and Power Allocation Using Water Filling Model for Underlay Cognitive Radio." Accessed December 21, 2022. http://crim.utem.edu.my/wp-content/uploads/2022/09/019-39-401.pdf.

Hattab, Ghaith, and Mohammed Ibnkahla. 2014. "Enhanced Pilot-Based Spectrum Sensing Algorithm." *2014 27th Biennial Symposium on Communications (QBSC)*. https://doi.org/10.1109/qbsc.2014.6841184.

Hu, Hang, Hang Zhang, Hong Yu, Yi Chen, and Javad Jafarian. 2015. "Energy-Efficient Design of Channel Sensing in Cognitive Radio Networks." *Computers & Electrical Engineering* 42 (February): 207–20.

Kabalci, Ersan, and Yasin Kabalci. 2019. "Cognitive Radio Based Smart Grid Communications." *From Smart Grid to Internet of Energy*. https://doi.org/10.1016/b978-0-12-819710-3. 00006 -5.

Kumar M, M., Sivakumar, V. L., Devi V, S., Nagabhooshanam, N., & Thanappan, S. (2022). Investigation on Durability Behavior of Fiber Reinforced Concrete with Steel Slag/Bacteria beneath Diverse Exposure Conditions. Advances in Materials Science and Engineering, 2022.

Khoshnevis, Hossein. 2012. "Pilot Signature Based Detection of DVB-T2 Broadcasting Signal for Cognitive Radio." *2012 Third International Conference on The Network of the Future (NOF)*. https://doi.org/10.1109/nof.2012.6464011.

Kockaya, Kenan, and Ibrahim Develi. 2020. "Spectrum Sensing in Cognitive Radio Networks: Threshold Optimization and Analysis." *EURASIP Journal on Wireless Communications and Networking* 2020 (1). https://doi.org/10.1186/s13638-020-01870-7.

Liu, Xin, Yongjian Wang, Yanping Chen, Junjuan Xia, Xueyan Zhang, Weidang Lu, and Feng Li. 2018. "A Multichannel Cognitive Radio System Design and Its Performance Optimization." *IEEE Access*. https://doi.org/10.1109/access.2018.2810061.

Maleki, Sina, Geert Leus, Symeon Chatzinotas, and Björn Ottersten. 2014. "To AND or To OR: How Shall the Fusion Center Rule in Energy-Constrained Cognitive Radio Networks?" In *2014 IEEE International Conference on Communications (ICC)*, 1632–37.

2015. "Energy-Efficient Distributed Spectrum Sensing with Combined Censoring and Sleeping." *IEEE Transactions on Wireless Communications* 14 (8): 4508–21.

Mukherjee, T., and A. Nath. 2015. "Cognitive Radio-Trends, Scope and Challenges in Radio Network Technology." *Aquatic Microbial Ecology: International Journal*. https://www.researchgate.net/profile/Asoke-Nath-4/publication/279530663_ijarcsms_cognitive_radio_tm_an_30_06_2015/links/5595613408ae5d8f3930ef3c/ijarcsms-cognitive-radio-tm-an-30-06-2015.pdf.

Neel, J. O. D. 2006. "Analysis and Design of Cognitive Radio Networks and Distributed Radio Resource Management Algorithms." https://vtechworks.lib.vt.edu/handle/10919/29998.

S. G and R. G, "Automated Breast Cancer Classification based on Modified Deep learning Convolutional Neural Network following Dual Segmentation," 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2022, pp. 1562-1569, doi: 10.1109/ICESC54411.2022.9885299.

Sun, Hongjian, Arumugam Nallanathan, Cheng-Xiang Wang, and Yunfei Chen. 2013. "Wideband Spectrum Sensing for Cognitive Radio Networks: A Survey." *IEEE Wireless Communications* 20 (2): 74–81.

Wu, Qingying, Benjamin K. Ng, and Chan-Tong Lam. 2022. "Energy-Efficient Cooperative Spectrum Sensing Using Machine Learning Algorithm." *Sensors* 22 (21). https://doi.org/ 10.3390/s22218230.