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Spectrum Forecasting TVWS Geolocation Database for Secondary-User TVWS Devices

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Abstract - This paper proposes a television white space (TVWS) database with forecasting capabilities using MATLAB. The researchers utilized a reinforcement learning program that would forecast the availability of different TV frequencies for a secondary user, which depends on their day and time of inquiry, location, and device. The forecasting accuracy is both dependent on the database and the AI. Provided that the database is frequently updated, the results of the forecast showed 100% accuracy. The reinforcement learning program and the forecasting program were both written in MATLAB's App Designer.

Index Terms – Reinforcement Learning, Television White Space Database, TVWS Spectrum Forecasting, Artificial Intelligence.

INTRODUCTION

TVWS communications is a growing technique and technology that brings new opportunities and challenges in maximizing frequency spectrum utilization. The opportunity is enormous for developing countries with regions with abundantly available spectrum in the TV band. Ismail, Kissaka, and Mafole indicated in their study that despite the considerable availability of TVWS in developing countries, there is a 30% average internet penetration. This outcome means a large population of people is still not connected to digital networks [1]. Implementation of TVWS for communications can be beneficial in rural and other underserved areas for developing countries. TVWS communications allows for a dynamic usage of the frequency spectrum. In their study, Alonso, Plets, Deruyck, Martens, Nieto, & Joseph found that using TVWS networks in suburban and rural scenarios has an energy efficiency of 9 to 12 times higher than LTE networks. This result shows that TVWS is a viable alternative in underserved areas [2].

In the Philippines, rural areas are left behind when it comes to connectivity. In an article by Inquirer Philippines, they partnered with ADB and Thinking Machines on Artificial Intelligence, Big Data, and Machine Learning for Development to map the digital poverty in the Philippines. They found out that access to sufficient Internet speeds worsens in rural areas [3]. This decline in access in rural areas leaves behind the people deprived of connectivity to the digital space.

The TVWS band can be used to provide super high-speed Wi-Fi (Wi-Fi 2.0) as a method to provide Internet connectivity to underserved areas. This Wi-Fi can provide high-speed rates of gigabits per second [4].

The TV spectrum has an abundance of white spaces, especially in underserved areas. With a TVWS database (TVWSDB), secondary users (SUs) can conveniently determine which bands of frequencies are available given a time and location for secondary use. The TVWSDB must be able to provide a list of available channels to inquiring SUs. Because the spectrum is dynamically changing due to primary user (PU) offairs or a variety of PUs in different areas, SUs who inquire to the TWSDB must be kept updated in proper time intervals, changing bands when needed to prevent interference with the PUs. Manually inquiring the database or continuously sensing band availability can be unreliable and inconvenient, especially since the spectrum is changing dynamically. Implementation of machine learning would help automate the inquiry and update process for SUs, given a reliable and periodically updating TVWSDB.

TVWS provides a solution for an alternative to establish wireless connections. The challenge here is to prevent interference with primary users (PU). In a study by Makgamatha, Zuva, and Masonta, they used a geolocation database that uses a protocol to access the available white space with a channel selection technique while meeting quality of service (QoS) requirements [5].

A Study by Aji, Wibisono, and Gunawan shows a study adopting TVWS technology for rural telecommunications solutions in Indonesia. According to them, there is a significant gap in telecommunication infrastructures between urban and rural areas, especially for developing countries. They argued that the utilization of TVWS is a fitting alternative technology for secondary purposes [6]. FCC and ECC already have standards that other countries may adopt.

With the 5G technology becoming mature, more demand for wireless spectrum resources. Because of this, dynamic spectrum access is a problem that should be solved. Research by Chen and Zhang designed a spectrum detection node with an embedded system that utilizes the TVWS frequency band. Their experiment showed that using a distributed electromagnetic spectrum information service platform based on signal characteristics can be used for accurate detection and system flexibility [7].

With the growing technology wireless of communication, more bandwidth-driven applications are emerging. Because of this, it is optimal to utilize the wireless frequency spectrum fully. With TVWS technology and its recent developments, the utilization of white spaces for secondary use is hope to become widespread. The work by I. Mustapha, Bakura, D. Mustapha, and Abbagana reviews approaches to TV white space and some deployments of TVWS technology in Africa [8]. They found out that TVWS is reliable and affordable, which is convenient for secondary use. It also can improve the economics of deploying wireless communications in underserved areas that are mostly rural, especially in developing countries.

Moreover, TVWS devices must dynamically change their operating frequency spectrum due to dynamically changing spectrum in different areas and times. This mechanism can be achieved by having configurable hardware and a good software design for the task. In this way, it also helps prevent interference when using PU frequencies during their non-operating hours.

A paper by Ma, Gao, Fu, Rong, Xiong and Cui

discussed the use of TVWS for maximizing the utilization of the spectrum to be used in different applications. They analyzed the spectrum utilization in London at different locations, both fixed and moving locations. They used machine learning to analyze the dynamic utilization of the spectrum based on their measurements, which allowed them to analyze how the spectrum is used in different channels, locations, and time instances, which helps exploit the white space for different applications [9].

Research by Rempe, Synder, Pracht, Schwarz, Nguyen, Vostrez, Zhao, and Vuran shows a prototype setup utilizing the TVWS spectrum with multiple cognitive radios and a TVWS database. An SU uses an available frequency and then updates the spectrum database, which other SUs see. Once the frequency becomes unavailable due to PU utilization, the cognitive radio must detect this and stops usage of the frequency while switching to another available frequency, updating the spectrum database once again. This operation is done through periodical database inquiry [10].

Hussien, Katzis, Mfupe, and Bekele created a mathematical framework for calculating the desired distances to prevent interference in co-channel and adjacent channel utilization of digital TV (DTV) frequencies. They utilized the ITU-R P.1546-5 and ITU-R P.1411-9 propagation models and HAAT values for the calculations in Ethiopia. They also determined the appropriate adjacent protection ratio in Ethiopian WSD networks, which is 27 dB [11].

The usage of TVWS requires standards and regulations to protect PUs. Sensing capabilities in WSDs are required to overcome this problem. However, this capability does not give accurate and systematic results and can be challenging to regulate. With a regularly updated TVWSDB containing all vital information needed, dynamic spectrum access can be monitored. Alejandrino, Concepcion II, Laugico, Trinidad, and Dadios investigated different WSD technologies available in the market and potential gaps in the TVWS implementation. They found out that the flexibility of the devices to operate in different topologies is one of the gaps. Different regulations in different countries may pose a problem [12].

A study in the Philippines by Morico, Porras, Judan, De Guzman, and Hilario analyzed TVWS availability in the Greater Metro Manila Area (GMMA). By creating propagation simulations that utilized the Okumura-Hata and Hata-9999 models, with spectrum measurements in a single route using a portable spectrum analyzer, results show a significant number of white spaces outside the GMMA can be utilized for secondary use [13].

The literature shows the lack of TVWS geolocation databases that have forecasting capability for SU, which this paper seeks to address. Section 2 discusses how the forecast was done, which is followed by the results in Section 3. The last section concludes the outcomes of the study.

METHODOLOGY

A reinforcement learning (RL) program was written as a MATLAB live script and tested. After multiple tests, the program was implemented in a MATLAB App Designer program where an SU can inquire about spectrum availability forecasts. The forecast can be classified into three terms. Short-term (ST), medium-term (MT), and long-term (LT). ST refers to the forecast within the day, MT for the next day, and LT for the next days in the future. The program was made to forecast the spectrum availability with respect to the SU's inquiry time, location, and transmission details based on SU's device. SU's device is assumed to be a fixed white space device limited to 4 watts EIRP. This value was based on FCC's fact sheet for unlicensed white space device operations [14].

Aside from the forecast results, the program utilized MATLAB's site viewer for propagation mapping. The PUs' propagation map utilized the Longley-Rice model, which is built-in MATLAB's Antenna Toolbox. SUs, on the other hand, utilized the free-space model due to its small coverage.

The database was created in Microsoft Excel, which was then imported and modified in MATLAB using MATLAB's different functions in manipulating data to make the written program more efficient in interacting with the database for training. Program schedules of PUs were obtained from different online sources such as official websites of the channel networks.

For testing the results of forecasts, during training, the learning data is compared with the PUs and SU interference calculations and the program schedule of PUs from the database. This step was made to ensure that the RL process yielded accurate decision-making for the SU.

RESULTS

Figure 1 shows the program made in App Designer. On the left, SU inputs contain time, location, device type (fixed 4W EIRP), and distances (in km) based on operating frequency, calculated using FCC's FM and TV Propagation Curve calculator.

On the right portion of the program is the spectrum information. A legend is seen from the GUI for the user's preference. The color of the lamp indicates the availability of a channel frequency. The number beside the lamp represents the number of hours the PU of a given channel is off-air. If the lamp shows that the channel is available but shows that the PU is on-air (0 hours result), it means that the SU that inquired is far enough from the PU that there is no interference if the SU decides to use the frequency.

Also on the right, at the bottom of the selected day, shows what type of forecasting was done. The day selected before the training button is pressed is considered as the ST forecast or the day of inquiry, in the figure's case, Sunday. A forecast day after the forecast inquiry is considered as the MT forecast. In this case, Monday is considered as the MT as seen from figure 2. LT forecast is finally from Tuesday to Saturday, a sample is seen in figure 3, a forecast on the Saturday, 6 days after the day of inquiry.

Depending on the day that the SU inquires for channel forecast, ST forecast is during the day of inquiry, MT is a day later the inquiry, and LT are the days beyond the 1st day after the inquiry. For example, if an SU would inquire on Sunday, ST forecast is on Sunday, MT is forecast on Monday, and LT would be Tuesday until Saturday. For the forecast to be accurate, the programming schedule must be kept updated.

The train button is required to be pressed before a forecast. The button runs the reinforcement learning training program in the background to get the available channels for the days of the week. A pop-up window shows the user that the training has been completed, as seen in Figure 4. The forecast status also turns green after the training from its initial state, red. After the training, the forecast button can now be pressed after selecting a day from the drop-down menu.



FIGURE 1 TVWS Forecast Program (ST)

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TVWS Forecast Program (MT)

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TVWS Forecast Program (LT)



FIGURE 4 Training Finished

Figure 5 and 6 shows the window that appears after the user clicks the "Display Map" button from the program. Figure 5 shows a zoomed-in version of the contour map to show how small the SU coverage is. When zooming out from Figure 6, the coverage of the PU can be seen. The contour map of the PU is based on MATLAB's built-in Longley-Rice model, while the SU, on the other hand, due to the small coverage area, uses the free-space model.



Secondary User Location and Coverage



FIGURE 6 Primary User Location and Coverage

To test the training results, that is, the Q-tables generated from the training, an algorithm was implemented after the main learning algorithm to test the correctness of the training data based on given conditions of the SU. The testing algorithm checks the Q-table, compares the values of accepting and denying a given channel, and compares these values to the case of the SU. Based on SU's parameters, how many hours a channel is available and whether the SU would interfere with the PU are checked and compared with the Q-table results.

The most optimal available channel is based on the channel's length of availability (PU off-air time) and whether the SU would interfere with the PU. If the PU's channel is not available and the SU is far enough not to cause interference, the PU's frequency is chosen as the most optimal channel. If the SU is within range of all the PUs, the most optimal channel is based on which PU's frequency offers the longest availability time for secondary use of their frequency.

Table 1 shows the accuracy result of the Q-Tables of 100 different SU cases on different days of the week. A 100% accuracy means that the machine learning algorithm could yield correct decision-making in forecasting the available channels for the given 100 SU cases.

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Table 1. Accuracy of Training Results

Day	Accuracy
Monday	100 %
Tuesday	100 %
Wednesday	100 %
Thursday	100 %
Friday	100 %
Saturday	100 %
Sunday	100 %

CONCLUSION

Implementing TVWS for communications, especially in underserved areas, maximizes the use of the TV spectrum. With the utilization of a TVWSDB with the implementation of RL, SUs can inquire about spectrum availability forecast in different terms. The authors created a MATLAB program that implements RL and TVWSDB that simulates an SU inquiring for spectrum forecasting. The forecasting can be categorized in three different terms, ST, MT, and LT. ST is during the current day of inquiry, MT the day after inquiry, and LT the remaining days beyond the week of inquiry. The RL process yielded a 100% accurate forecast based on given conditions. However, given that program schedules of PUs change over time, in actual implementation practice, it is recommended to keep the database updated.

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