Methodology for Characterizing Spectrum Data by Combining Quantitative and Qualitative Information

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Abstract. Wideband spectrum data can provide information on how large portions of the spectrum are being used. Spectrograms are typically used to visualize this data. The interpretation of the spectrogram (e.g., identification of bands and patterns) is left to the user, requires significant domain knowledge and is extremely time consuming. In this paper, we present a methodology for combining quantitative and qualitative information to identify channels and changes in spectrum occupancy. Channel identification and change detection algorithms are applied to real spectrum data collected over several years on two different measurement systems in Chicago. These analyses were then used to formulate queries to a knowledge graph implemented on a neo4j graph database. The results of the queries validated the channel identification and provided validation and explanation of the changes detected. This methodology was tested on measurement data from 470–698 MHz.

Keywords: Spectrum measurements · Knowledge graph · Graph database · Change detection

1 Introduction

Wideband spectrum data can provide information on how large portions of the spectrum are being used. Spectrograms are typically used to visualize this data. The interpretation of the spectrogram (e.g., identification of bands and patterns) is left to the user, requires significant domain knowledge and is extremely time consuming. We seek to combine the quantitative analysis of the data with qualitative information to enable continuous, large-scale analysis and to make this type of analysis and interpretation more accessible to those with limited domain knowledge.

Multiband spectrum measurements are spatiotemporal datasets that provide information about spectrum utilization in space, frequency, and time. The characteristics depend on how the frequency band has been allocated (i.e., what type of transmission is legally permitted), how it is used in practice and where the measurements are taken (i.e., what signals can be observed at the given measurement location). In order to effectively characterize true dynamics of spectrum measurements, it is necessary to

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explore the underlying structure of the data and automatically provide a descriptive depiction. The goal of characterization is to combine the analysis of the quantitative measurements with qualitative information about how the spectrum is allocated and used in time and space.

Wideband data spans a large number of frequency bands while narrowband usually focuses on small frequency range. For example, one of the Illinois Tech wideband measurement systems captures signals from 30 MHz to 6 GHz, resulting in the sampling of approximately 240K frequencies. Since there are different rules that govern each band, the data must first be separated into bands. Bands can be defined at different levels of abstraction depending on the how the spectrum is allocated. Often bands are subdivided into channels that may or may not have a common use and set of users. Each frequency band has its own unique time-varying characteristics.

Spectrum occupancy measures the percentage of time that a given frequency band or channel is utilized over a given time in each location. The measured utilization of different bands can be found to range from highly utilized, through sporadically used, to not used at all. For example, the TV band includes relatively stable signals coming from transmitters that are stationary and continuously or near-continuously transmitting. Bands that are allocated for Wi-fi and Land Mobile Radio (LMR) introduces mobility plus spatiality. When interpreting the quantitative band occupancy calculation, it is necessary to also consider qualitative or contextual information about the location of potential transmitters and the physics of the signals transmitted. Some signals may be out of range of the measurement system, and some may not be captured due to the measuring system configuration. In this paper, we present a methodology for combining quantitative and qualitative information to identify channels and changes in spectrum occupancy.

2 Background and Related Work

2.1 Spectrum Measurements

Spectrum measurements play a key role in understanding how spectrum is utilized in space, frequency, and time. The design and configuration of the measurement system influences the quality and type of data collected. The Illinois Tech Spectrum Observatory has been using two measurement systems to collect long-term data on spectrum use in Chicago. System 1 measures the spectrum from 30 MHz–6 GHz and System 2 measures the spectrum from 44–900 MHz. Both of the systems use energy detection sensing with specific resolution bandwidths (RBW). The RBW is the bandwidth of a single spectrum measurement obtained during a specific sampling interval. RBW determines frequencies contributing channels based on channel widths. Each system is configured through a band plan which partitions the measurement range into bands where sampling resolution can be specified. The System 1 band plan configures 29 bands where there are 8001 frequencies sampled in each band. There are more than 240,000 frequencies sampled resulting in 93 MB of data per day. The System 2 band plan configures 8 bands with high resolution sampling (1 kHz or 3 kHz) resulting in approximately 200,000 frequencies sampled generating 23 GB of data per day. This work focuses on the analysis of measurements from 470–698 MHz collected from System 1 and System 2. Given the different configurations of these systems as specified above, the resulting data is quite different.

2.2 Analysis with Spectrograms

Analysis of spectrum data usually starts with spectrograms or waterfall charts which are typically used to give a high-level view of spectrum occupancy data. For these charts, time/sweep is represented on the y-axis, frequency is on the x-axis (MHz) and power (dBm) is shown through color. The spectral occupancy is estimated based on noise floor which is a threshold to determine if the measured power exceeds the threshold indicating that a valid signal that was detected. For wideband measurements spanning the 30 MHz to 6 GHz range, the noise floor fluctuates by several dB power levels. Hence, different noise floors must be calculated and used in each sub-band.

Spectrograms allow for the visualization of channels, utilization, and changes/patterns. Spectrograms at different time scales can help identify daily, weekly, and yearly patterns and trends. Figure 1 shows a spectrogram of a band (406–698 MHz) selected from the System 1 spectrum measurements from 2017. From the spectrogram, the channels, and a general sense of occupancy (i.e., whether the channels are occupied throughout the whole year or not) can be determined. This paper describes a methodology to automatically extract this type of information.

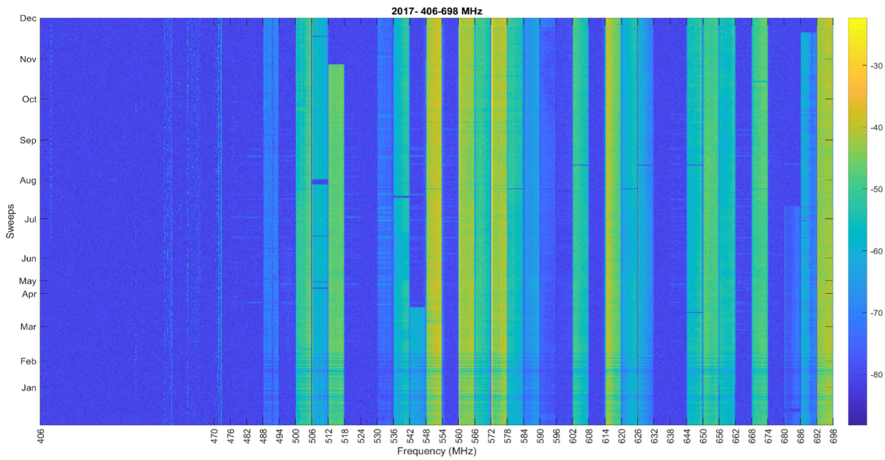

Fig. 1. Spectrogram of 406–698 MHz during 2017.

2.3 Contextual Information

To interpret the visualization of the measurements, contextual information is needed. For example, when looking at the spectrogram in Fig. 1, one is interested in knowing not just that there are channels, but what the channels are used for. To do this one must first find out how the frequencies of interest have been allocated. Since spectrum is a natural resource, each nation decides how the spectrum will be allocated and utilized within its borders. Since this paper involves spectrum measurements collected in Chicago, we focus on the United States spectrum allocation.

In the United States, the National Telecommunications and Information Administration (NTIA) manages the federal spectrum and the Federal Communications Commission (FCC) manages the non-federal spectrum. Figure 2 shows part of the Frequency Allocation Chart. This chart gives a high-level view of how the spectrum is allocated. One or more radio services are indicated in the chart. The narrow, colored band along the bottom of the chart indicates whether the spectrum is federal exclusive (red), non-federal exclusive (green) or federal/non-federal shared (black). Most importantly, this tells us where (i.e., NTIA or FCC) we can find more detailed information about the spectrum usage. In Fig. 2 we can see that the frequencies from 470–512 MHz are reserved for non-federal use and are shared by three different radio services, Broadcast Television, Land Mobile and Fixed.

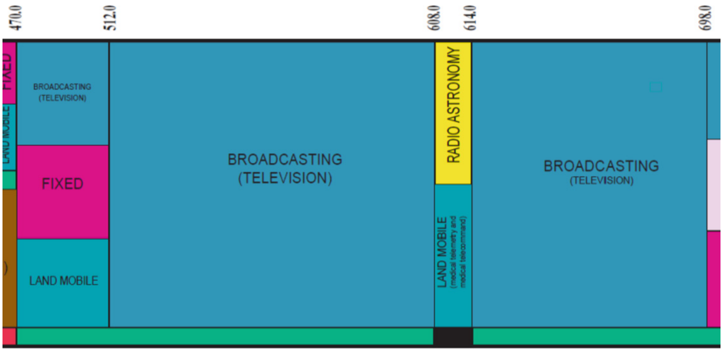

Fig. 2. Snapshot of 470–698 MHz band from the US frequency allocation chart.

A full table of frequency allocations in the US can be found at [1]. Frequency allocations are done per band, where bands are contiguous A band plan defines various characteristics related to the use of spectrum in a specific frequency range. The band plan defines the frequency range to which it applies, parameters related to the use of the spectrum, such as the width of channels, boundaries of sub-blocks within the band, guard bands (if any), etc., and the applications that can use those channels and sub-blocks. The band plans and table of frequency allocations shown in Fig. 3 encode information regarding both what an individual frequency assignment means, as well as the radio service to which it applies.

470-608	470-512 FIXED LAND MOBILE BROADCASTING NG5 NG14 NG66 NG115 NG149	Public Mobile (22) Broadcast Radio (TV)(73) LPTV, TV Translator/Booster (74G) Low Power Auxiliary (74H) Private Land Mobile (90)
	512-608 BROADCASTING NG5 NG14 NG115 NG149	Broadcast Radio (TV)(73) LPTV, TV Translator/Booster (74G) Low Power Auxiliary (74H)

Fig. 3. Snapshot of 470–698 MHz band from the US frequency allocation table.

For non-federal spectrum, the FCC maintains data on authorized licenses and publishes regulatory documents defining the proper usage of spectrum in a given geo-temporal context. FCC databases are the primary source of information on current non-federal spectrum allocations. Since the FCC is the regulating authority defining spectrum usage, the FCC periodically goes through a process of rule-making that defines how frequency allocations will change and what regulations apply. Title 47 of the Code of Federal Regulations (CFR) defines rules and regulations regarding telecommunications services in the United States. All rules and regulations pertaining to the FCC are defined there. For example, the CFR contains information on how to calculate parameters such as Height Above Average Terrain (HAAT) and Effective Radiate Power (ERP).

Federal documents are a repository of spectrum information and invaluable in understanding spectrum usage. However, in some cases, secondary sources can be useful sources that provides the spectrum information in a semi-structured manner. For example, spectrum in the 600 MHz to 700 MHz which was previously used for broadcast TV was made available for other applications [2]. Following the incentive auction TV, channels in the 600 MHz were moved down to lower frequencies to channels that were vacated by other applications. Other channels in the sub-600 MHz also changed as part of the band plan changes. This process overall was called the Digital TV repacking.

Table 1. Chicago area broadcast digital TV repacking plan (channel changes).

Old channel number	Old channel frequency (MHz)	New channel number	New channel frequency (MHz)
20	506–512	26	542–548
27	548–554	23	524–530
29	560–566	33	584–590
31	572–578	24	530–536
32	578–584	18	494–500
34	590–595	28	554–560
35	596–602	32	578–584
36	602–608	21	512–518

(*continued*)

Table 1. (*continued*)

Old channel number	Old channel frequency (MHz)	New channel number	New channel frequency (MHz)
38	614–620	35	596–602
39	620–626	20	506–512
40	626–632	27	548–554
43	644–650	34	590–596
44	650–656	22	518–524
47	668–674	25	536–542
21	512–518	*Did not change*	
45	656–662	*Did not change*	
49	680–686	*Did not change*	
50	686–692	*Did not change*	
51	692–698	*Did not change*	

While details of changes in the band plan due to Digital TV repacking are available through the FCC, the information is fragmented across multiple documents and is often buried in complex, verbose documents. In such a scenario, secondary sources can provide the required information in a semi-structured fashion. The situation is further complicated by there being different repacking plans in different markets. Rabbitears is a website that provides the repacking information in a semi-structured format [3]. When that information is correlated with other secondary sources—Over-the-air-Digital-TV [4] and RadioReference [5]—a complete repacking band plan can be constructed for a market area. Table 1 demonstrates the repacking changes in the Chicago market area [6].

2.4 Related Work

The majority of usable spectrum is allocated in the Unites States [1, 7] and across the world [8, 9] at the same time that the demand for wireless spectrum continues to expand rapidly. A great deal of recent work has been devoted to applying clustering techniques towards spectrum analysis including real-time characterization of spectrum states and spectrum prediction [10–17]. Our previous work [18, 19] has shown the value of semantic information towards spectrum analysis studies. Spectrum occupancy modeling continues to develop as a vibrant field [20, 21].

The TxMiner [22] system has been shown to have the capability to characterize spectrum occupants in an unsupervised fashion using a learning algorithm called Rayleigh-Gaussian Mixture Model (GMM). This gives a very basic but good way of identifying active radio transmitters based on measurements. In [23], Agarwal et al. investigate time series models for occupancy prediction of stationary bands like TV and cellular bands. SpecInsight [24] is an intelligent wideband spectrum sensing and analysis system that learns the characteristics of the signals in each frequency band and adjusts the sensing parameters to maximize detection. A significant innovation is a technique to detect both low and high occupancy signals. Although this system reduces the knowledge necessary for configuration and analysis, a semantic framework could increase the utility of both the data and the analysis results by facilitating linkage with other spectrum measurements and analysis results as well as external data.

In the Dynamic Spectrum Access space there has been some research effort towards modeling spectrum usage, but we do not consider the existing approaches to be aligned with information modeling. While there has been considerable amount of research in the information modeling and knowledge graph space [25–27], since the concept of a knowledge graph was introduced originally by Google [28], to our knowledge, knowledge graphs have not been applied towards getting a deeper understanding of spectrum usage and analysis.

3 Approach

3.1 Quantitative Analysis

Wideband measurements will capture many bands which in turn may contain multiple sub-bands or channels. When there is activity in bands and/or channels, it is quite easy to grasp the organization of the band from a spectrogram as shown in Fig. 1. Along with the structure of the band, we are interested in characterizing the dynamics of the band and in particular identifying changes in the dynamics. Although both the structure and changes can be identified from the visualizations, generating and inspecting spectrograms manually is quite time intensive and is not feasible for continuous and/or wideband measurements. This research seeks to automate the identification of the band structure, characterization of usage, and identification of changes in the identified sub-bands or channels. This paper focuses on identification of the structure and change detection using the measurements from the frequency band 470–698 MHz.

To start with, we use a simple algorithm to determine the structure in the band. Contiguous frequencies with similar measurements are grouped together to form a channel. This is based on the assumption that frequency measurements within a channel will have correlated activity. In this study, we used the mean energy in a frequency over 24 h (one day) as the basis for grouping frequencies. For a given frequency band, the range of mean energy values is divided into buckets based on a threshold which is calculated based on the minimum and maximum value of the range. Correlated frequencies will be grouped together in each bucket. The buckets can be aggregated to give a coarse-grain characterization of the energy level of the correlated frequencies. This roughly corresponds to the colors in the spectrogram. As shown in the Table 2, given the number of correlated frequencies and the resolution bandwidth, the width of the identified channels can be estimated.

Table 2. Snapshot of channels identified on 01-Jan-2017.

Start freq (MHz)	End freq (MHz)	Total freq	RBW (KHz)	Estimated channel width (MHz)
500.06	505.974	163	36.5	5.9495
512.032	517.946	163	36.5	5.9495
536.086	541.962	162	36.5	5.913
614.014	619.963	164	36.5	5.986

Once the channels have been identified and characterized, the focus is on getting a general understanding of the channel dynamics. The first step in this process is to detect when changes have occurred. Change detection techniques detect abrupt changes in time series data by comparing the current measurements to established usual measurements. In this work, an offline change detection mechanism is used [29]. Given the estimates of the channels, we can focus on the center frequencies as a reasonable representation of the channel. Therefore, we focus on the time series of energy measurements of the center frequencies. The type of dynamics identified by the change detection algorithm depends on the time-scale of the features used for change detection. For example, when we use the daily mean energy as input, the minimum changes that can be detected are on a daily basis. More precision can be attained by using finer grain means (e.g., hourly) or by using an online change detection algorithm. There are many possible reasons for changes in the measurements including changes in the spectrum usage (scheduled or unscheduled), changes in allocation and problems with the measurement system. For example, short-term dynamics are possible for TV stations that turn off periodically and long-term dynamics can occur due to allocation changes.

3.2 Modeling of Qualitative Information

In our previous work [30], we proposed an architecture for unifying the different types of spectrum information so that knowledge may be aggregated and reasoned over. This architecture is based on knowledge graphs. A method for modeling various types of information as knowledge graphs was developed. The knowledge graphs are implemented in the Neo4j graph database platform [31]. One of the primary knowledge graphs was implemented with data from the FCC License View API [32]. The FCC License View API provides access to data contained in several FCC licensing databases which collectively represent a majority of publicly available license information for non-federal spectrum. This knowledge graph provides an easy mechanism for making sense of spectrum data in a particular geographic, temporal, and application context. The knowledge graph makes the task of querying and visualizing information much easier than querying the datasets via existing web-based search tools and APIs.

3.3 Combining Quantitative Analysis Results with Qualitative Information

To get an understanding of how the spectrum is being used, a combination of quantitative and qualitative information is needed. The measurements provide information about how the spectrum is actually being used. This includes information about how the measured frequencies are organized into channels as well as characterization of the channel activity and dynamics. To validate and explain the results of the quantitative analysis, qualitative is information is needed to provide the context needed for understanding. The whole process is visualized in Fig. 4, starting with the observations. As seen from Fig. 4, observations include measurements along with configuration parameters of the measurement system such as band plan and RBW. After the data is analyzed to identify the channels, the knowledge graph in the graph database is queried to validate the estimated channel identified. A similar process is used when the analysis of the center frequencies within channels is used to detect changes. The changes detected are then used to formulate queries to try to determine the cause of changes detected. Given that our current knowledge graph is focused on licensing and allocation information, the only changes that can be validated or explained at this time are changes in licensing or allocation. As detailed earlier, this includes the repacking of broadcast TV channels to provide more spectrum for cellular services.

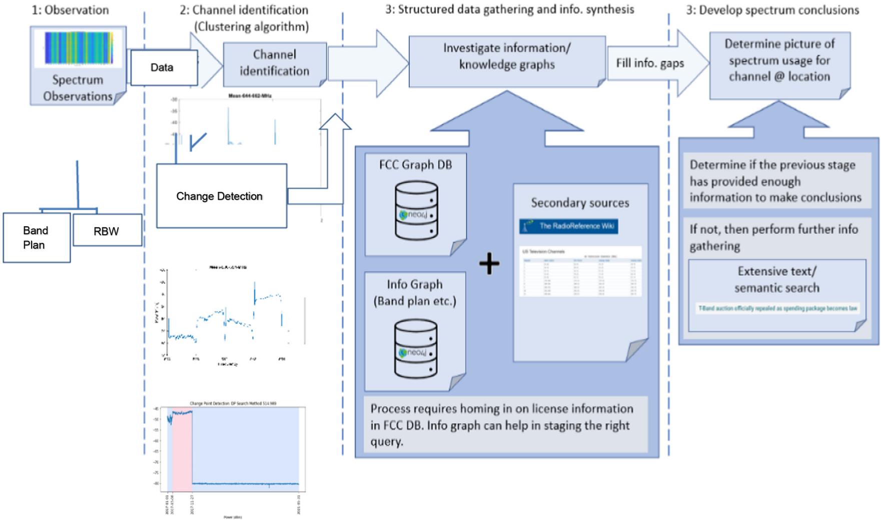

Fig. 4. Process flow diagram of methodology.

4 Results

The research presented in this paper involved the analysis of the 470–698 MHz block from system 1 and 470–700 MHz block from system 2. From Fig. 2, we can see that this block is mostly allocated for broadcast TV. Thus, the channels identified are TV channels. We chose to start in this band because TV transmission is generally continuous thus the channels can be easily detected. Even in this band, we found some challenges and interesting dynamics with the repacking and reallocation. Table 3 shows the channels identified from one day of data from the years 2017–2019 from system1 and from one day of data from 2021 from system 2. Channels with very low signal strength are difficult to identify with our algorithm.

Table 3. Summary number of channels identified.

	2017	2018	2019	2021
Actual-channels	25	21	19	16
Identified channels	22	21	17	13

Table 4 gives an example of some of the channels identified based on the measurements captured using system 1. The number of frequencies grouped is included in the table and using the RBW, the minimum estimated channel width is calculated. Table 5 gives an example of some of the channels identified based on the measurements from system 2. Note that the RBW for system 2 is much smaller than the RBW for system 1 so the sampled frequencies are much closer (only 3 kHz apart). The actual TV channels are 6 MHz so these estimates are close. In Fig. 1, you can observe variations in the channels across the frequencies and at the boundaries between channels. Also, given that these estimates are based on how the systems are configured to sample the frequencies, we do not expect to get an exact value, even in the best case. We are looking for an estimate that we can compare to the response from the knowledge graph.

Table 4. Example of channels identified using system 1 data

Start freq (MHz)	End freq (MHz)	Total freq	RBW (KHz)	Min. estimated channel width (MHz)
488.052	493.928	162	36.5	5.913
500.06	505.974	163	36.5	5.9495
506.12	511.85	158	36.5	5.767
512.032	517.946	163	36.5	5.9495
536.086	541.962	162	36.5	5.913
542.108	547.876	159	36.5	5.8035

Table 5. Example of channels identified using system 2 data

Start freq (MHz)	End freq (MHz)	Total freq	RBW (KHz)	Min. estimated channel width (MHz)
494.208	499.827	1785	3	5.355
500.148	505.875	1910	3	5.73
506.127	511.905	1911	3	5.733
512.115	517.882	1923	3	5.769
518.134	523.834	1874	3	5.622
524.083	529.96	1960	3	5.88

```
ExecutionEngine execEngineTV = new ExecutionEngine(digitalTVbp);

int freqSearch = 491008000;      //491.008 MHz being searched

ExecutionResult execResult = execEngine1.execute("
            MATCH (fa:frequency_assigned) WHERE f.frequency_assigned <= " + freqSearch + "
            MATCH (fu:frequency_upper) WHERE f.frequency_upper >= " + freqSearch + "
            MATCH (fa)<-[*1]-(c:channel)-[*1]->(fu)
            RETURN c, fa, fu;
            "));
```

Fig. 5. Query on TV band for the channel frequency range and channel number.

After identifying the channels, validation is done through the knowledge graph implemented in the graph database. A Java code fragment including the query is shown in Fig. 5. Since the frequency searched in this example is 491.008 MHz, we can look at the spectrum allocations shown in Figs. 2 and 3 and see that the frequency falls within a block that is shared by Broadcast TV, Fixed and Land Mobile Radio services. Since we have implemented the digital TV band plan, we started by querying that knowledge graph and found a match. The highlighted line shows that the channel, lower frequency and upper frequency of the channel are returned when center frequency is searched from the channel. The results confirm that the 491.008 MHz is part of a 6 MHz TV channel from 488–494 MHz.

To determine changes in the identified channels, the change detection algorithm was run on the sampled frequency nearest to the center of each channel. This algorithm was run on 53 months of data from 01-Jan-2017 to 31-May-2021. The spectrogram in Fig. 6 shows a comparison of one day of data from 2017–2019. The data from each day is stacked to visualize the changes. When comparing the visualization from 2017 (on the bottom) to the one from 2019 (on the top), it is evident that there are several channels that are no longer active. There is one channel 524–530 MHz channel where there is new activity in 2019. This stacked visualization gives a general idea of the what changed, but does not provide any information about when the changes occurred. The change detection algorithm identifies the day when the change happened. Figure 7 shows the date when channel 514.989 MHz changed.

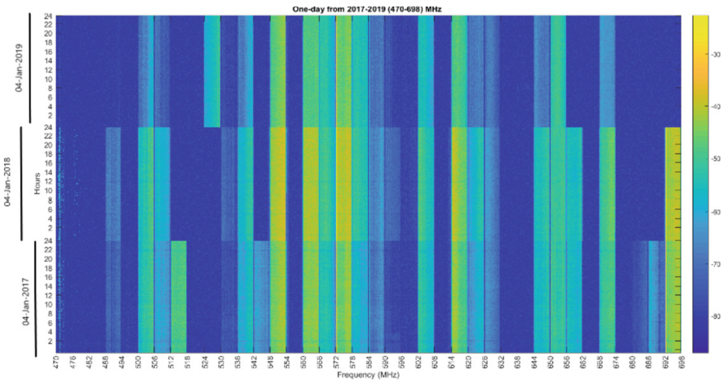

Fig. 6. Spectrogram cascaded three days from 2017–2019

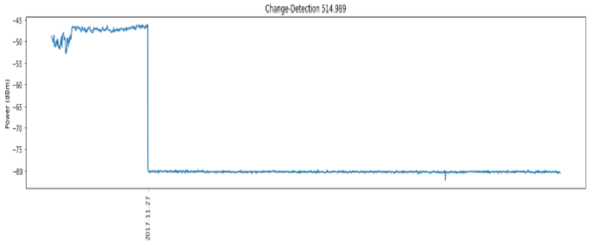

Fig. 7. Change detection for channel 514.989 MHz

The TV band repacking began in 2018 and concluded by July 2020. Figure 8 shows the changes due to repacking. This process was initiated to free up the 600 MHz band for the broadcast incentive auction. As a result of the repacking, the 600–700 MHz band was reallocated to cellular and public safety use. The changes can be seen from spectrogram shown on the right side of Fig. 8 and in Fig. 9. The new and different activity in the 600 MHz band is evident.

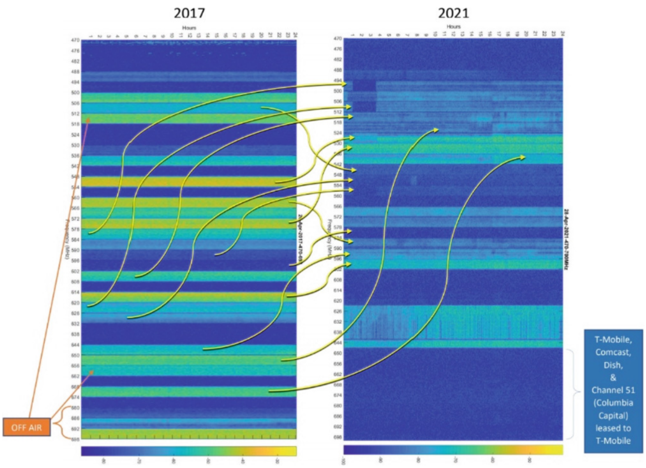

Fig. 8. TV channel changes as a result of Digital TV repacking.

Fig. 9. Spectrogram of 470–700 MHz band in April 2021

5 Conclusion and Future Work

This paper describes a methodology for combining quantitative and qualitative information to characterize spectrum data. Channel identification and change detection algorithms are applied to real spectrum data collected over several years on two different measurement systems in Chicago. These analyses were then used to formulate queries to a knowledge graph implemented on a neo4j graph database. The results of the queries validated the channel identification and provided validation and explanation of the changes detected. This methodology was tested on measurement data from 470–698 MHz. This block is comprised of mostly TV bands which are generally stationary and have continuous transmission. Although this is a very straightforward case, there are significant challenges to automate all of the steps. This result is a first, significant step towards automated analysis of spectrum measurements incorporating both quantitative and qualitative information.

Ongoing work involves extending the methodology to more challenging cases which can eventually span all types of bands. This includes expanding to consider more complex features and also different time scales. Spectrum behavior is challenging to interpret, and prediction of usage is driven by many factors such as planned and unplanned events, weather and human protocols.

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