HF spectrum activity prediction model based on HMM for cognitive radio applications


ABSTRACT

Although most of the research on Cognitive Radio is focused on communication bands above the HF upper limit (30 MHz), Cognitive Radio principles can also be applied to HF communications to make use of the extremely scarce spectrum more efficiently. In this work we consider legacy users as primary users since these users transmit without resorting to any smart procedure, and our stations using the HFDVL (HF Data+Voice Link) architecture as secondary users. Our goal is to enhance an efficient use of the HF band by detecting the presence of uncoordinated primary users and avoiding collisions with them while transmitting in different HF channels using our broad-band HF transceiver.

A model of the primary user activity dynamics in the HF band is developed in this work to make short-term predictions of the sojourn time of a primary user in the band and avoid collisions. It is based on Hidden Markov Models (HMM) which are a powerful tool for modelling stochastic random processes and are trained with real measurements of the 14 MHz band.

By using the proposed HMM based model, the prediction model achieves an average 10.3% prediction error rate with one minute-long channel knowledge but it can be reduced when this knowledge is extended: with the previous 8 min knowledge, an average 5.8% prediction error rate is achieved.

These results suggest that the resulting activity model for the HF band could actually be used to predict primary users activity and included in a future HF cognitive radio based station.

1. Introduction

Standard HF communications make use of the ALE (Automatic Link Establishment) protocol [1,2] which is frequently presented as an example of a primitive form of cognitive radio. It is based on a Listen Before Transmit strategy to access the spectrum and makes use of sensing, probing and monitoring techniques to assess channel utilisation and channel quality. But the ALE protocol has two major drawbacks: it does not manage the spectrum as a whole, in a wide-band sense, but as individual channels; and, additionally, it does not manage the link in a transparent way to the user, as it only concerns the link establishment leaving the intelligent management to higher layers, usually outside of the radio equipment. Moreover, even if HF stations make use of ALE protocol, there are multiple collisions between them because they
only transmit on their assigned channels that are expected to be available according to the experience of the radio operator.

Considering the previous issues, it is likely that as long as cognitive radio principles are introduced in HF stations, the radio frequency spectrum could be exploited in a more efficient way as HF stations will become aware of their surrounding environment and learn from it. In order to achieve such improvements in the band, these cognitive stations shall have the capability to change their operating parameters in order to adapt their transmissions to the available spectrum holes which are to be predicted by using the acquired knowledge.

In cognitive radio systems two types of users are distinguished: primary and secondary users. Primary users are those users that are holders of a license for a particular frequency band and therefore shall have prime access to it. Whereas, unlicensed users transmitting in that band are taken as secondary users as they are allowed to make use of it, but required not to interfere with communications coming from primary stations.

Due to the trans-horizon behaviour of HF communications and the limited bandwidth where all HF users around the world can transmit, the difference between primary and secondary users relies on the smart and cognitive capabilities of the HF user, so, in this work we will consider the primary ones to be the legacy users which transmit without resorting any smart procedure and consequently will interfere in our communications both on transmitter and receiver sides. On the other hand, our stations using the HFDV (HF Data+Voice Link) architecture [3], which are also licensed for certain HF bands, hereafter will be considered as secondary users of the accessible frequency channels. Consequently, our stations must be able to predict when the primary users start and finish their transmissions, as they can interfere with transmitter and/or receiver sides, in order to send our own data packages by filling silence slots within primary transmissions. To do this, we shall use our broad-band HF transceiver [4] to select those channels predicted as available. This architecture would be able to enhance the efficient use of the HF band and the performance of our HF communication system, provided that a suitable model for HF can be found.

A model of the primary user's dynamics in the band shall be extremely useful to make the best from the acquired knowledge in predicting the activity of the primary user in the channel. A predictive model is derived in this work for the HF band based on a set of Hidden Markov Models. It has been trained and validated on real data from the HF band as a first step towards a fully operative cognitive radio scheme for the band occupancy.

Attending to the modelling and detection problems, Hidden Markov Models (HMMs) are widely used for speech recognition [5] but more recently they have also been used on cognitive applications for primary user detection and prediction, where they have achieved remarkable results. A spectrum detection system based on several HMMs, each trained for a particular signal spectrum, was presented in [6]. Besides, channel state prediction models based on HMMs were proposed in [7,8]. The one addressed in [7] could only predict the channel state for observation sequences of a 1 symbol period or 2 symbols period; and could not carry out the prediction of non periodic sequences as real measurements from a frequency band actually are. Furthermore, the model proposed in [8] was based on Higher-Order HMM and took into account the latency between spectrum sensing and Wi-Fi data transmissions. This model achieved a low average error rate with a prediction span of five time slots of 2 μs each. As we will further discuss, this prediction span is smaller than the prediction span for our model in HF communications and the average error rates obtained cannot be compared to the ones presented here, as Wi-Fi data transmissions have also a smaller length than most common HF communications, which may last for several seconds.

Despite these previous contributions, most of the research in cognitive radio is related to communication bands above the HF band. Quite recently Koski and Furman introduced the challenges and opportunities of applying cognitive radio principles to HF communications in [9] and provided an overview of the concepts that could be considered for the next-generation ALE to introduce cognitive capabilities in [10]. However, to the best of our knowledge, no proposal for a real or simulated cognitive system for the HF band has been published yet.

1.1. Outline

The rest of the paper is organised as follows: the first part includes a description of the challenges of applying cognitive radio principles in HF communications in Section 2 and a brief introduction to Hidden Markov Models in Section 3.

The second part describes the processes involved in the implementation of the HF primary user dynamics model detailed in the block diagram in Fig. 1. First, the acquisition of the measurements of the HF band is described in Section 4. Later, the measurement processing is depicted in Section 5, while observed sequences are then classified and segmented according to the criteria enunciated in Section 6.

The proposed HF primary user dynamics model is described in Section 7, where the training and validation processes are presented; whereas the prediction scheme developed and tested on top of this model is described in Section 8. Finally, conclusions on this work are drawn in Section 9.

2. Applying cognitive radio principles to HF communications

Long distance communications are feasible in the HF band (3–30 MHz) thanks to the use of the ionosphere as a passive reflector. As the link establishment depends on a natural media such as the ionosphere, its propagation characteristics change depending on the time of day, atmospheric conditions, solar radiation and meteorological phenomena. But besides its propagation characteristics, the main limitation of any HF link is related to its use since there are multiple collisions of uncoordinated users around the world. Therefore, it is important to remark on other
3. Hidden Markov models

HMMs are a powerful and robust tool for modelling stochastic random processes as they are able to model a large variety of processes achieving high accuracy with relatively low model complexity. They have been extensively used in a myriad of signal processing applications during the last 20 years, mainly for fitting experimental data onto a parametric model which can be used for real-time pattern recognition, and to make short-term predictions based on the available prior knowledge [5].

A Hidden Markov Model is defined as a doubly embedded process with an underlying stochastic process that is not observable. This hidden process (state) can only be evaluated through another set of processes that produce sequences that actually can be observed [5]. An HMM for discrete symbol observations is defined by the following elements:

- **A**: State transition probability distribution matrix $A = \{a_{ij}\}$ of size $N^2$ where $N$ is the number of states in the model and
  $$a_{ij} = P[q_{t+1} = S_j | q_t = S_i], \quad 1 \leq i, j \leq N. \quad (1)$$
  The set of individual states is $S = \{S_1, S_2, \ldots, S_N\}$ and the state at time $t$ is denoted as $q_t$.

- **B**: The observation symbol probability distribution for state $i$, $B = \{b_i(k)\}$, where
  $$b_i(k) = P[O_t = V_k | q_t = S_i], \quad 1 \leq i \leq N; \quad 1 \leq k \leq M, \quad (2)$$
  $O_t$ is the observation at time $t$ and $M$ is the number of distinct observation symbols per state. The observation symbols correspond to the physical output of the system being modelled and are denoted as $V = \{V_1, V_2, \ldots, V_M\}$.

- **π**: The initial state probability distribution $\pi = \{\pi_i\}$ where
  $$\pi_i = P[q_1 = S_i], \quad 1 \leq i \leq N. \quad (3)$$

- **O**: Observation sequence
  $$O = O_1 O_2 \cdots O_T \quad (4)$$
  where each observation $O_t$ is one of the symbols from $V$ and $T$ is the number of observations in an observed sequence.

Thus, a complete definition of an HMM involves: two model parameters ($N$ and $M$), the specification of the observations symbols and the specification of $A$, $B$ and $\pi$. In practise the compact notation used for an HMM will be

$$\lambda = (A, B, \pi). \quad (5)$$

Regarding the structure of the transition matrix $A$, HMMs can be classified into different groups. In an ergodic or fully-connected HMM every state of the model can be reached from any other state in the model after a finite number of steps. However, transitions between HMM's

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**Fig. 1.** Block diagram for the training, testing and usage of the proposed HF primary user dynamics model in classification and prediction tasks.
states are most frequently limited. An example of these models is the left-right or Bakis HMM which has the property that as time increases the state index either increases or stays the same. Such a model was introduced to fit signals which changed over time in a successive manner, and is characterised by its transition matrix which forbids non-causal transitions within the models, i.e. its state transition coefficients have the property

\[ a_{ij} = 0, \quad j < i \]  

(6)
as no transitions are allowed to states whose indexes are lower than that of the current state. Another relevant characteristic of a left-right HMM is that the state sequence must begin in state 1 and end in state \( N \), so the initial probability distribution has the following property

\[ \pi_i = \begin{cases} 0 & \text{if } i \neq 1 \\ 1 & \text{if } i = 1. \end{cases} \]  

(7)

Additionally, from an implementation perspective, such simplification introduces both a hard restriction and a relevant simplification for the model to be derived, as the number of parameters in the transition matrix decreases dramatically by almost a factor of 2.

Three major tasks must be fulfilled for a Hidden Markov Model defined as (5) to be useful in practical applications [5]:

1. **Evaluation**: Given an observed data sequence and a set of models to be compared, the probability that the provided sequence was produced by each of them, \( P(O|\lambda_k) \), is to be computed as the cumulative product of the likelihood obtained by each evaluated sample. This is calculated through the sum of the so called, terminal forward variables, \( \alpha_T(i) \), defined in the “forward–backward” algorithm [5]. From the perspective of the Neyman-Pearson lemma, this can be considered as a scoring problem, in which the resulting scores will be used to decide which of the models fits the observed sequence better (i.e. obtained the largest accumulated likelihood value).

2. **Decoding**: Given an observation sequence, we choose a state sequence that is optimal in some meaningful sense. By doing this, we try to uncover the hidden part of the model according to some criteria. The most widely used criteria is to find the best state sequence that maximises the probability \( P(O|\lambda) \) using the well-known Viterbi algorithm [11].

3. **Learning**: The parameters of a particular model are adapted in order to maximise its likelihood when a set of sequences which correspond to the class it models is observed. The learning task is also referred to as the training of the model in which we attempt to find the model parameters which best describe the observed sequence (the training sequence). An iterative procedure such as the Baum–Welch method [5] is used to locally maximise the likelihood of the model defined as \( P(O|\lambda) \).

Sections 7 and 8 are devoted to describe how the three tasks were developed in order to train and test the model, and also, to use them for prediction using a trained model.

4. **Measurement acquisition**

Real measurements from the HF band have been recorded to train and test the proposed model based on HMMs. The acquisition setup was located at IDETIC facilities in Las Palmas de Gran Canaria and it is shown in Fig. 2. We have used our own broad-band transceiver [4] followed by a Vector Signal Analyzer (VSA) [12] and SystemVue Software [13], both from Agilent Technologies, to collect the time data from the Yagi antenna and convert it into frequency data (spectrum) by means of the Fast Fourier Transform (FFT) with the required characteristics. Several parameters, such as span, resolution bandwidth and number of bins for the FFT, must be adjusted while a suitable balance between them has to be observed to obtain the desired spectrum information. As it is shown in Fig. 2, our broad-band HF transceiver was required in the measurement system to collect data from the antenna which was then sent onto the Vector Signal Analyzer as the sensitivity of the VSA was not high enough and could not be used to reliably identify most of the HF signals in the band.

Sequential measurements of the 14 MHz amateur band were carried out during three days in June and September 2011 with the acquisition setup shown in Fig. 2. These spectrum power measurements were collected in sample batches with a duration of 10 min, separated by intervals of 15 min. We have restricted our analysis to this band due to the limited bandwidth of our antennas, though the high-activity and the presence of all kinds of transmissions, both data and voice, observed within this band seemed to be a remarkable scenario to test and validate the proposed model.

Furthermore, depending on the day, the 14 MHz amateur band has different degrees of activity. There is normal activity on weekdays as can be observed in Fig. 3, while a huge amount of activity can be found at weekends, especially in those when amateur contests are scheduled, as can be observed in the collected data shown in Fig. 4.

The 14 MHz amateur band is in frequencies from 14,000 to 14,350 kHz and it is divided into three sub-bands:

- 14,000–14,065 kHz: CW signals.
- 14,065–14,100 kHz: Digital modulations such as PSK31 or 2-FSK.
- 14,100–14,350 kHz: SSB analog modulations.

In order to acquire spectral information from the whole band we have selected 14,175 kHz as the central frequency and a span of 500 kHz, though the collected span by VSA was actually wider than 500 kHz. With these parameters we obtained measurements of the amateur band and also channels outside of it that correspond to other radio stations as it can be seen in the examples in Figs. 3 and 4. Given that all kinds of transmissions and activities take place in the acquired bandwidth, the 14 MHz band measurements are fairly representative of the main activities and transmissions that can be found in the whole HF band.

In these measurements the 3 kHz channelisation can be identified, but some of the detailed HF characteristics in Section 2 cannot be directly identified as these are strictly power measurements. For example, a power increase in a particular channel can be observed in these measurements,
Fig. 2. Measurement acquisition setup located at IDeTIC facilities in Las Palmas de Gran Canaria, Spain.

Fig. 3. Example of the acquired HF spectrum of the 14 MHz band with central frequency 14,175 kHz, span of 500 kHz and a duration of 10 min. Normal activity scenario.

Fig. 4. Example of the acquired HF spectrum of the 14 MHz band with central frequency 14,175 kHz, span of 500 kHz and a duration of 10 min. High activity scenario.

but we are not able to distinguish if it is due to a collision between users or it is due to a strong interference close to our broad-band transceiver.

Finally, once measurements were obtained, they were processed to obtain sequences of '1' and '0' values which correspond to occupied or available channel samples,
respectively, as detailed in Section 5. These sequences will be used as training and test sequences for the proposed model.

### 5. Measurement processing

The information captured by the VSA was processed to obtain the spectrum power of the whole acquisition band. Both frequency and time domain processing were applied to the collected data to obtain a time-frequency representation of the activity in each channel. Samples representing the mean power in a 3 kHz channel within a time slot of two seconds were obtained in this pre-processing step.

In the frequency domain, the collected spectrum is uniformly divided into channels of 3 kHz bandwidth as in the HF band; and the mean power is computed for each channel. Additionally, as the VSA computes the FFT of the wide-band measurement of 500 kHz span every two seconds approximately, the time resolution was defined in samples of approximately two seconds long. Finally, to complete the pre-processing step and obtain a reliable representation, time integration of the samples of the previous eight seconds of each channel is performed in order to best characterise the time evolution of the transmissions and avoid samples which represent the nulls of the HF channel and the typical impulsive noise present in this band.

Once channels are processed in time and frequency domains, the signal detection problem is set out to transform the power samples into normalised values. For this purpose, two hypotheses were defined:

\[ H_0 : x[n] = w[n] \quad n = 1, \ldots, N - 1 \quad (8a) \]

\[ H_1 : x[n] = w[n] + s[n] \quad n = 1, \ldots, N - 1. \quad (8b) \]

\( H_0 \) holds when there is only noise, \( w[n] \), in the channel at sample \( n \), while \( H_1 \) is true when there is a signal, \( s[n] \), in the channel with additive noise at sample \( n \). The detector that maximises the detection probability for a given false alarm probability is defined through the likelihood ratio test formulated in (9) as specified by the Neyman–Pearson lemma [14]

\[ \mathcal{L} (x) = \frac{p (x; H_1)}{p (x; H_0)} > \gamma \quad (9) \]

where \( p (x; H_1) \) is the probability distribution function for occupied-channel samples, \( p (x; H_0) \) the probability distribution function for only-noise samples and the threshold \( \gamma \) of the detector is derived from the false alarm constraint

\[ P_{FA} = \int_{\gamma}^{\infty} p (x; H_0) \, dx = \alpha. \quad (10) \]

The way to assess such a detector is to plot the Receiver Operating Characteristics (ROC) curve, which represents the detection probability \( P_D \) versus the false alarm probability \( P_{FA} \) for different thresholds \( \gamma \). Given the constrained false alarm probability \( \alpha \), the corresponding value of the threshold that maximises the detection probability can be found just by using the estimated ROC curve.

For these acquired measurements the probability distributions for both hypotheses, \( p (x; H_0) \) and \( p (x; H_1) \), are estimated by computing the normalised histogram of the power of only-noise samples and occupied-channel samples, respectively. These estimations are plotted in Fig. 5 and as a result, threshold \( \gamma \) can be defined. Furthermore, in order to evaluate the ROC curve, the only-noise probability distribution has been fitted to a normal distribution \( N(\mu_0, \sigma_0) \) with mean \( \mu_0 = -58.82 \), standard deviation \( \sigma_0 = 3.23 \) and probability density function

\[ p (x; H_0) = \frac{1}{\sigma_0 \sqrt{2\pi}} e^{-\frac{(x-\mu_0)^2}{2\sigma_0^2}}, \quad (11) \]

whereas the occupied-channel probability distribution has been fitted to a generalised extreme value distribution with location parameter \( \mu = -47.125 \), scale parameter \( \sigma = 3.882 \), shape parameter \( \xi = -0.015 \) and probability density function

\[ p (x; H_1) = \frac{1}{\sigma} \left( 1 + \frac{x - \mu}{\sigma \xi} \right)^{-\frac{1+\xi}{\xi}} e^{-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}} \quad (12) \]

As it can be observed in Fig. 5, the estimated probability distribution for hypothesis \( H_1 \) can not be completely fitted to the proposed GEV distribution, but it is the best accurate fitting as it allows us to define the asymmetry of the estimated probability distribution from the acquired measurements. As opposed to the normal distribution, the GEV distribution can be used to fit data with non-zero skewness.

Once both distributions are fitted, the false alarm probability \( (P_{FA}) \) and the detection probability \( (P_D) \) are computed to represent the analytic ROC plotted in Fig. 6 where

\[ P_{FA} = \int_{\gamma}^{\infty} p (x; H_0) \, dx \]

\[ = \int_{\gamma}^{\infty} \frac{1}{\sigma_0 \sqrt{2\pi}} e^{-\frac{(x-\mu_0)^2}{2\sigma_0^2}} \, dx = Q \left( \frac{\gamma - \mu_0}{\sigma_0} \right) \quad (13) \]

\[ P_D = \int_{\gamma}^{\infty} p (x; H_1) \, dx \]

\[ = \int_{\gamma}^{\infty} \frac{1}{\sigma} \left( 1 + \frac{x - \mu}{\sigma \xi} \right)^{-\frac{1+\xi}{\xi}} e^{-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}} \, dx \]

\[ = 1 - e^{-\left(1+\xi\frac{x-\mu}{\sigma}\right)^{-\frac{1}{\xi}}} \quad (14) \]

and \( \gamma \) is the detection threshold.

As it can be observed in Fig. 6, the analytic ROC could represent the mean behaviour of the acquired measurements as some experimental ROC curves are above the analytic ROC whereas others are below it.

### 6. Data classification and segmentation

Acquired wide-band measurements have been translated into binary observation sequences where each one represents a 3 kHz HF channel for ten or nine minutes. Each sequence has ‘0’ and ‘1’ values which represent only-noise...
samples or occupied-channel samples, respectively. Subsequently, these observation sequences are segmented into smaller sequences with a duration of one minute and classified in order to reduce the variability of the trained sub-models (see Section 7).

As it can be observed in Figs. 3 and 4, different degrees of activity can be identified in the acquired channels. There are several channels which are almost unoccupied for long-time slots, while other channels remain occupied for the same amount of time and could not be used to transmit. Finally, there are other channels which could be used by a secondary user to transmit and make an efficient use of the band. So, we propose in this work a classification of the observation sequences prior to the stochastic modelling of the primary user’s dynamics. This classification is based on the degrees of activity observed in the acquired measurements and the secondary user’s behaviour in a cognitive radio system, that is:

- **Available channels** where the secondary user can transmit.
- **Unavailable channels** where a primary user is in the band and the secondary user cannot transmit.
- **Partially available channels** in which there are time intervals during which the secondary user can transmit until a primary user appears.

Observation sequences of ten and nine minutes long were segmented into one minute-long sequences as it can be seen in Fig. 7. These short sequences could be classified as ‘Available’, ‘Unavailable’ and ‘Partially available’ channels and encoded as \{1, 2, 3\}, respectively, to reduce the complexity of the model to be trained.

The criteria followed to classify the observation sequences of each channel is based on the maximum time that a secondary user will need to transmit a data frame. Two thresholds were defined: one for minimum percentage of occupation by a primary user in unavailable channels, in such a way that the secondary user can transmit its maximum length data frame, and another for the maximum percentage of occupation in available channels. In order to derive both thresholds, it is necessary to get the worst case of channel occupation as secondary users in HF data communications. This worst case scenario comes from assuming a maximum length for data frames to be transmitted by the secondary user. In this contribution, the frame of maximum length defined by the NATO Standardisation Agreement STANAG 5066 [15] has been considered for our stations as secondary users. This standard establishes the profile for professional HF data communications and defines frames, called D-PDU, that have 46 bytes of overhead and up to 1023 bytes of user data. Most HF data communications use a data rate of 600 bps or 1200 bps, and, with these parameters, the longest D-PDU frame resulting would last for 14.25 s (1069 bytes at 600 bps), which represents the worst case of channel occupation by the secondary user to be considered in our work.

Therefore, observation sequences with at least 45 s occupied within a minute were considered to belong to the unavailable channels group as secondary users will not be able to transmit the largest frame during the remaining 15 s. Similarly, available channels were defined as those observation sequences with a maximum of 15 s occupation in one minute. Finally, the rest of the observation sequences were classified as partially available channels where secondary users could transmit for less than 45 s to avoid collisions with primary users.
7. HF primary user dynamics model

In this contribution Hidden Markov Models were used to model the primary users activity dynamics in the 14 MHz band. As it was described in Section 1, such a model could be used by our HFDVL stations, acting as secondary users, to predict the presence of a primary user, preventing interferences in their own transmissions. Therefore, this prediction would be the main source of information to avoid collisions with licensed users of the band, and consequently, to make the best possible use of the available frequency channels.

Once data from the HF band has been processed and classified, the activity model can be defined and trained. Due to the proposed classification of the observation sequences, the model has a hierarchical structure and is defined as an ergodic HMM with three states interconnecting three underlying submodels, one for each class (i.e. available, unavailable and partially available channel) as it can be seen in Fig. 8. These type of structures are commonly used in HMM based generative models as the one presented in [16] for burst error characterisation.

Each submodel was trained with a set of one minute-long observation sequences from the corresponding class as previously defined (see Section 6) to derive a suitable model for the group at hand. Consequently, the first submodel was meant to characterise available channel sequences, the second submodel for unavailable channel sequences and the third one for partially available channel sequences. These submodels were implemented as left-right HMMs as the particular structure of the transition matrix they exhibit is quite suited to model the time evolution of the samples in the observation sequences, definitely better than ergodic models can, and with a reduced number of parameters to be trained.

In the end, the proposed model for primary user’s dynamics was built through the combination of a high-level, ergodic HMM with three states, each of them corresponding to available, unavailable or partially available channels respectively, and a set of three left-right submodels. Each state in the upper model emits an observation sequence of a minute long which is generated by the submodel corresponding to that state. To simplify the training and evaluation of the high-level model, this was trained as an independent HMM where each state only emits one single value representing the state, independently from the scores provided by the low-level submodels. That is, state $S_1$ only emits symbol ‘1’ and it represents the observation sequence generated by submodel 1. This also happens for states $S_2$ and $S_3$ emitting symbols ‘2’ and ‘3’, respectively. So, the observation matrix for the high-level ergodic model, $B$, would actually be the identity matrix. Under this specification, observation symbols generated by the high-level model would be also the transitions between its states, that is, the transitions between the underlying submodels. When the whole model is evaluated, the symbols for each state {1, 2, 3} correspond to the observation sequences generated by the respective submodels for each of these states {1 (Available channels), 2 (Unavailable channels), 3 (Partially available channels)} respectively and not these symbols.

Moreover, while submodels were trained to characterise one minute-long observation sequences from available, unavailable or partially available channels, the high-level model was trained to characterise the evolution of a particular channel for ten and nine minute-long sequences, in which states are classified according to one minute-long sequences.

Once defined, the proposed model was trained and validated with the acquired data of Section 4.

7.1. Training of the model

The learning problem was established in terms of the optimisation of the HMMs’ parameters (5) through the maximisation of $P(O|\lambda)$, that is, to identify the model...
which maximises the probability that the observation sequences used for training were actually generated by
the model. The Baum–Welch algorithm [5], based on
the Expectation–Maximisation method, was used to train
both submodels and the high-level model. Randomly
initialised matrices were used for the first iteration of
the Baum–Welch method, as no prior knowledge on the
structure of the sequences was provided, and the amount
of collected data seemed to be quite enough.

Due to the differences in the selected structures for the
high-level model and the three submodels, two different
training protocols were followed. Whereas the number of
states of the high-level model was pre-fixed – 3 – due
to the prior classification of the observations, the number
of states for each submodel still had to be chosen. On
the one hand, in training the proposed ergodic high-level
model, our major concern was related to the initialisation
of the values due to the ergodic structure itself. This
structure had to be trained to be independent on the
initial point, assuming that its execution could begin at any
time, i.e. any of the three defined states could be the first.
Thus, the transition matrix A, containing the estimated
probability of going from one state to another regardless
of the previous history, was initialised with different random
seeds to reinforce the model stability, and trained on
previously classified observation sequences including one
minute-long available, unavailable and partially available
segments.

On the other hand, the non-ergodic, left-right structure
of the submodels largely reduced the complexity and
cost for their training; unlike the high-level model for
which no specific structure could be established. The
number of states for the submodels, designed as left-
right HMMs including three-states-long transitions (i.e. on
each intermediate state, the incoming and outgoing
transitions is equal and fixed to 4), was chosen according
to the procedure previously described, based on the
likelihood scores computed on every one minute-long
observation sequences. For these submodels, matrices A
and B were randomly initialised with a common seed,
while π was initialised as in (7) due to the left-right
structure which forces the models to begin at the first
state. Different configurations for these models including
20–45 states were trained with their own one minute-long
observed sequences including binary samples containing
information on channels’ occupancy: the available channel
submodel was trained with all sequences classified as
available channels, and the same was done for unavailable
and partially available channel submodels.

Once trained, submodels’ accumulated likelihood scores
were obtained according to the evaluation task de-
scribed in Section 3, and the model with the maximum
likelihood (highest P(O|λ) among all trained models) was
identified. However, a normalisation model built from
the combination of all samples included was artificially in-
troduced to normalise the likelihood scores and prevent
spurious effects during their estimation. This slight modi-
fication causes the former likelihood values to be bounded
and behave as averaged likelihood ratios resulting from
comparing different models to a common one, and there­
fore allows positive and negative values. However, to com­
pare the scores from two different models, the subtraction
of these scores would still provide a relative cumulative
log-likelihood ratio measure, independent from the inter­
mediate artificial model introduced. Their assessment was
conducted by attending to the results depicted in Fig. 9.
Focusing on the curves included in this figure and corre­
sponding to unavailable and partially available channel
submodels, it should be noticed that the log-likelihood
scores reach a local maximum for the configuration in
which forty states were included, while log-likelihood
scores corresponding to the available channel submodel
were very small (see curve scale) for any number of states.
Consequently, according to this result a suitable left-right
HMM to model sequences included in the latter group
could be built on any number of states from 20 to 45 with­
out major differences. However, from a practical point of
view we realised that if all submodels included the same
number of states their comparison would be easier once
the whole model was trained and used for prediction.
Therefore, all submodels discussed hereafter are left-right
Hidden Markov Models including forty states and up to
three-states-long transitions as the one in Fig. 10.

Being the number of states for the submodels ade­
quately chosen, each of the models was trained over a
sample including 70% of the observed sequences corre­
sponding to it, and the model parameters maximising
P(O|λ) were then identified. The Baum–Welch algorithm
was applied to randomly initialised HMM matrices A and
B with the same seed used in the previous step. Matrices
were obtained after ten iterations of the algorithm to pre­
vent over-fitting. The rest of the acquired sequences were
evaluated on the proposed models to re-estimate likeli­
hood scores and then compared to the values obtained
on the training sequences to check that the models did
not over-fit the training data. We specifically checked that
these matrices represent stable models, that is, there is a
transition with a high probability in each row of the tran­
sition matrices and if the transition probabilities along
the matrix are analysed, the final state is always reached for
any observation sequence.
Viterbi algorithm was developed to identify the state dynamics model. Prediction scheme based on the HF primary user were the same as the transition sequences due to the initial values contained the observation sequences for the high-level model.

Following procedure was designed to predict whether a activity of primary users in a particular HF channel. The main goal of this model is to make an efficient occupancy sequences found on the HF band.

To emit random sequences statistically close to the real one, it would be able to provide a pseudo-random sequence generator, it would be able to emit sequences such as the ones used in this test. Furthermore, if we think of it as a pseudo-random sequence generator, it would be able to emit random sequences statistically close to the real measurements used for its training, i.e. similar to the actual occupancy sequences found on the HF band.

The developed architecture shall operate according to the flow shown in Fig. 11. While a secondary user is sensing different channels in order to select the one that can be used to transmit without interfering with a primary user, it shall process the spectrum measurement corresponding to the last minute and use it as an observation sequence to evaluate the three submodels for available, unavailable and partially available channels. By evaluating the “forward-backward” algorithm, their likelihoods are computed and, instead of choosing the submodel with highest likelihood like in the evaluation process, the resulting probabilities can be used in the high-level model as updated entries for its observation matrix.

Subsequently, the “forward-backward” algorithm is evaluated in the high-level model on the sequence of states corresponding to the prior T minutes and the three possible states for the next minute are evaluated: {1 (Available channels), 2 (Unavailable channels), 3 (Partially available channels)}. The state with the highest likelihood will be considered to be the predicted state for the channel in the next minute.

The average error rate of the prediction model with a prediction span of one minute is plotted in Fig. 12. Due to the time restriction on the data acquisition process which lasted for 10 min, most of the test sequences actually have a duration of nine minutes and thus, the maximum time span of the acquired knowledge is 8 min.

In addition to the global performance of the prediction model, performances for normal and high activity in the HF band are also presented in Fig. 12. As it was previously stated, the 14 MHz amateur band has a different behaviour depending on the day: there is a huge amount of activity at weekends, especially when amateur contests are scheduled, whereas there is a normal amount of activity on weekdays. Both situations have been considered in the training stage of the HF primary user dynamics model, so, the trained model will be able to predict whether a primary user will be present in the channel or not within the next minute in both situations.

As shown in Fig. 12, the global performance, when the secondary user has listened the previous minute and no past information is available, the model has an average error rate of 10.3% but, as the acquired knowledge of the channel increases, this error rate decreases monotonically. In fact, if the secondary user could access the channel state
memory of the previous 8 min, the error rate is reduced to a 5.8%.

For high-activity environments, the average error rate of the prediction model increases to 16% when the secondary user has only listened the previous minute and it is reduced to 9.6% if the secondary user has a channel state memory of the previous 8 min. However, the average error rate decreases (respect to the global performance) to 8.7% in normal-activity environments with a channel state memory of the last minute and decreases to 4.7% when the secondary user has listened the previous 8 min.

8.1. Use of the HF spectrum activity prediction model

A comparative study of ALE-based stations with HFDVL stations using the proposed HF prediction model in terms of link capacity is presented in this section to illustrate the prospects for using the proposed HF prediction model. First of all, it is important to remark on the differences that would exist between ALE-based stations and cognitive stations using the HF prediction model. Both stations will transmit when the channel is available and will not transmit when the channel is occupied by another user, but the main difference relies on the decision to transmit or not when a channel is partially available. The ALE-based station will transmit or not depending on what it has listened to at the start of the time slot: if the channel is occupied it will not transmit but if the channel is free, it will transmit even though a primary user could try to transmit later on the same slot. However, the HFDVL-based station using the HF prediction model will be able to detect
In terms of link capacity, this fact will cause a higher capacity achievement with the HFDVL stations than the ALE-based stations when channels are partially available. The link capacity increase would then be related to the average percentage of time that the channel is actually available, provided that this is classified as a partially available channel. This situation takes place 69.73% of the time in our measurements. So, assuming that our HFDVL stations are transmitting an OFDM signal with 60 data subcarriers in a 3 kHz bandwidth HF channel [3], and that the noise power density is the same as the estimated for only-noise samples in Section 5, the capacity could be estimated as

\[ C \simeq \frac{1}{L} \sum_{i=1}^{L} \left( \sum_{k=1}^{N_c} \Delta f \log_2 \left( 1 + \frac{|H_i(k)|^2}{\sigma_N^2} \right) \right) \]

where \( L \) is the number of measurements used for the computation, \( N_c \) is the number of OFDM subcarriers, \( \Delta f \) is the subcarrier spacing, \( H_i(k) \) is the channel frequency response at subcarrier \( k \) and measurement \( i \) and \( \sigma_N^2 \) is the noise power density, resulting in an estimated link capacity of 22,378 bits per second.

The capacity achievements of both stations will highly depend on the number of channels classified as partially available. If most of the sounded channels by both stations are available and only a few partially available, there will not be a great difference between both stations. Nevertheless, if most of the sounded channels by both stations are classified as partially available, the HFDVL-based station with the HF prediction model will use the acquired knowledge to transmit in the spectrum holes without colliding with a primary user and, consequently, achieve a higher link capacity than the ALE-based station.

Merely as an example to illustrate this capacity increase, if we assume that channels are independent and there are 2 available channels, 1 occupied channels and 6 partially-available channels, the HFDVL station using the HF prediction model will achieve a global link capacity of 

\[ 4 \times C + 2 \times (0.6973\times C) \]

bits per second whereas the ALE-based station will achieve a lower global link capacity that will depend on the probability of collision if the ALE-based station decides to transmit in a partially available channel.

9. Conclusions

In this contribution we have proposed a primary user dynamics model for the HF band based on Hidden Markov Models. Due to the regulatory bandwidth restrictions and propagation characteristics of this frequency band, the use of this model to make predictions within the next minute of the activity in a particular channel is considered to be extremely helpful for cognitive stations acting as secondary users like our HFDVL based stations or any other standard HF modem using a 3 kHz HF channel.

The proposed model has been trained and validated with real measurements collected from the 14 MHz amateur band, and is built from three interconnected submodels which describe three types of channels: available channels, unavailable channels and partially available channels. Finally, we have used this model to predict the activity in a channel within the next minute and achieved an average 10.3% error rate when the acquired knowledge of the channel has a duration of one minute and reached an average 5.8% error rate when this knowledge is extended to the previous 8 min.

Furthermore, the use of this prediction model in our HFDVL-based stations would improve the efficient use of the band as it could be able to detect the spectrum holes and transmit when the predicted channel is classified as partially available. Due to the fact that the ALE-based station would not transmit due to the high collision probability with a primary user in a partially available channel, it has been shown that the HFDVL-based station could reach a higher channel capacity than an ALE-based station.

These results are very promising and show the possibilities of applying these prediction techniques in HF scenarios by means of cognitive radio principles.

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