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**Intelligent Spectrum Management based on Transfer Actor-Critic Learning for Rateless Transmissions in Cognitive Radio Networks**

**Abstract:**

This research targets an intelligent spectrum mobility in cognitive radio networks (CRNs). Spectrum mobility could be real spectrum handoff (i.e., the user jumps to a new channel) or wait-and-stay (i.e., the user pauses the transmission for a while until the channel quality becomes good again. An optimal spectrum mobility strategy needs to consider its long-term impact on the network performance, such as flow throughput and packet dropping rate, instead of adopting a myopic scheme that optimizes only the short-term throughput. We thus propose to use a promising machine learning scheme, called Transfer Actor-Critic Learning (TACT), for the spectrum mobility strategies. Such a TACT-based scheme shortens a user’s spectrum handoff delay, due to the use of a comprehensive reward function that considers the channel utilization factor (CUF), packet error rate (PER), packet dropping rate (PDR), and flow throughput. Here, the CUF is estimated by a spectrum quality modeling scheme, which considers spectrum sensing accuracy and channel holding time. The PDR is calculated from NPRP M/G/1 queueing model, and the flow throughput is estimated from a link-adaptive transmission scheme, which utilizes the rateless codes. Our simulation results show that the TACT algorithm along with the decoding-CDF model achieves optimal reward value in terms of Mean Opinion Score (MOS), compared to the myopic spectrum decision scheme.

**Existing System:**

The spectrum decision taken should maximize performance within the entire communication session instead of just maximizing the performance for a short phase. Motivated by this, we turn towards intelligent spectrum management(iSM) by integrating channel selection metric (CSM) scheme with the machine learning algorithms. Spectrum handoff strategy based on long-term optimization model, such as Q-learning used in our previous work, can achieve high-throughput multimedia transmissions over CRN links. Qlearning can determine the proper spectrum decision actions based on the comprehensive SU state estimation (including PER, queueing delay, etc.). However in the beginning, the SU does not have any prior knowledge of the CRN environment. Initially it starts with the trial-and-error process,explores each action in each state, and achieves optimal state after some iterations. Thus Q-learning could take considerable time to converge to an optimal, stable solution.Particularly in CRN, the channel access time is limited. When more number of states and actions are defined for a particular learning process, the learning process will be prolonged.

**Proposed System:**

We have proposed several transfer learning algorithms in the field of Machine learning for CRNs, such as apprenticeship learning. However, our previous teaching algorithms still have some areas to be improved. We should avoid the exact imitation of the expert node’s policy since each node in the network may experience different channel conditions. Therefore, it is necessary to consider a transfer learning algorithm which can use learned policy from the expert SU to build its own optimized learning model by fine tuning the expert policy according to the channel conditions it experiences. We accomplish this using state-of the art algorithm - Transfer Actor Critic Learning (TACT). More importantly, we connect the Q-learning with TACT to receive the learned policy from the expert node, which greatly enhances the teaching process without introducing much overhead on the expert node.