QoE Estimation and Prediction using Hidden Markov Models in Heterogeneous Access Networks

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Abstract—Quality of Experience (QoE) based handoffs in heterogeneous access networks (HAN) necessitates accurate QoE estimation and prediction. The current approaches to QoE-aware handoffs are limited. These approaches either lack the availability of underlying probing mechanism or lack the availability of QoE estimation and prediction mechanism. In this paper, we propose, develop and validate a novel method for QoE estimation and prediction using passive probing mechanisms. Our method is based on hidden Markov models and multi-homed mobility management protocol. Using extensive simulations and experimental studies, we show that our method achieves QoE estimation accuracy of 100% and prediction accuracy of 97% in HAN without using additional probe packets for QoE estimation and prediction.

Index Terms—hidden Markov models, mobility management, multi-homing, handoff, QoE.

I. INTRODUCTION

Emerging wireless technologies has led to the proliferation of mobile devices and Internet use. Mobile devices such as tablets and smart-phones can connect to heterogeneous access networks (HAN) using plethora of wireless technologies such as WiFI or 4G. Users usually associate some expectations while accessing applications on their mobile devices. For example, they expect 4G network to perform better than 3G or WLAN. It was envisioned by Gustafsson and Jonsson [6] that while roaming in HANs, users will always be best connected and networks will meet their expectations. These expectations along with the quality of service they perceive dictate their quality of experience (QoE) [14].

QoE provisioning in HAN can be achieved using handoffs [8]. For efficient QoE-aware handoffs, there are several challenges that need to be tackled. Firstly, there is a need to develop an efficient network path probing mechanism for all network interfaces of the mobile node (MNs) that require minimal bandwidth overhead. Secondly, methods for accurate QoE estimation and prediction are required that consider time-varying HAN conditions [8],[16]. The current approaches to handoffs, namely [4], do not explore the benefits of QoE estimation and prediction while making handoffs. Further, approaches such as [16] and [10] simply assume the availability of underlying network path probing mechanism to facilitate handoffs. These assumptions are unrealistic and can severely hinder QoE provisioning in HAN [8],[16]. We assert that current approaches to QoE-aware handoffs lack efficient network path probing mechanism and methods for accurate QoE estimation and prediction in HANs.

Our contributions: In this paper, we propose, develop and validate a novel end-to-end mechanism for accurate QoE estimation and prediction (considering VoIP application) in HAN using passive probing, which is missing in the state-of-the-art. Our method is based on hidden Markov models (HMM) [11] and multi-homed mobility management protocol (M-MIP) [1]. To the best of our knowledge, the method proposed in this paper is the first to integrate QoE estimation and prediction capabilities directly into a mobility management protocol.

The rest of the paper is organized as follows. Section II presents the related work. Section III presents our proposed approach. Section IV presents the results. Finally, section V presents the conclusion.

II. RELATED WORK

Hidden Markov models have been successfully applied to model both wired and wireless network characteristics. For example, Liu, Matta and Crovella [7] considered HMMs and a pair of round trip time (RTT) probe packets to classify different types of losses in wireless networks. However, their scheme was limited to classification of congestion and wireless losses and did not consider users' QoE.

Tao and Guérin [15] estimated Internet path performance using HMMs. They considered active probing mechanism to estimate and predict packet losses using HMMs. However, their work was limited to wired networks and did not consider stochastic wireless network impairments such as fading, wireless network congestion and handoffs. Further, active probing requires additional probe packets which increases bandwidth and monitory costs. Compared to their scheme, we develop a passive probing mechanism based on HMMs and M-MIP to estimate and predict users' QoE in mobile computing scenarios. Our scheme does not require additional probe packets and can minimize network bandwidth and monitory costs.

Andersson *et al.* [4] presented an approach for access network selection. Authors considered the running variance metric (RVM) and relative network load (RNL) [2], [1] to determine impairments such as wireless network congestion. Based on RNL scores, appropriate network was selected. However, they did not consider the problem QoE estimation

and prediction. Compared to [4], our method can directly estimate and predict users' QoE.

Piamrat *et al.* [10] and Varela and Laulajainen [16], presented methods for QoE-aware network selection based on PSQA metric [12]. The PSQA metric mainly consider numerical values such as percentage of packet loss and mean loss burst size to output mean opinion score (MOS) based on Random Neural Networks (RNN). The problem with RNN is that it requires large number of training samples for performing prediction. This limits their ability to learn continuously on-line in an unsupervised manner. Further, their scheme assumes the availability of underlying probing scheme for QoE prediction which is unrealistic in real-life settings.

Compared to the state-of-the-art, our proposed scheme directly integrates with M-MIP [2]. It eliminates the need for additional probe packets in the network thus saving both bandwidth and monitory cost. It discovers the QoE states automatically based on OWD/RTT delay and then estimate and predicts these states very accurately in stochastic HAN conditions.

III. SYSTEM MODEL

Accurate QoE estimation and prediction requires correct path probing mechanism [8],[16]. This is vital for HAN which are prone to network level impairments such as network congestion and handoffs. The mobile nodes (MN) and routers can either use active or passive path probing mechanisms for QoE estimation and prediction. In case of active probing, probe packets are injected into the network to mimic application traffic flows between two end-systems. Based on delay and packet losses observed using these probes, network states can be estimated, network congestion and handoff. However, this mechanism while being beneficial, leads to an increase in bandwidth requirements. In passive probing, the application flow itself is used to estimate path quality statistics without requiring additional probe packets. Thus, bandwidth savings are made while estimating the network path quality. However, this mechanism is application specific. In this paper, we argue for application independent passive probing mechanism which can be used to monitor all the network interfaces of MNs, simultaneously.

In HAN, multi-homed mobility protocols such as M-MIP [1] are considered for application session continuity using handoffs. These protocols implement signalling mechanisms such as binding update (BU) and binding acknowledgement (BA) packets to handle events like packet flow redirection. In this paper, we propose to use BU and BA packets as probe packets. We then propose to use HMMs trained using one-way delay (OWD) or RTT delay calculated using these probe packets to estimate and predict QoE for VoIP applications (using the ITU-T E-model [5]). In doing so, our method eliminates the need for additional probe packets generated on all the network interfaces. Further, this method remains independent of any application type, packet size and packet send and receive frequency.
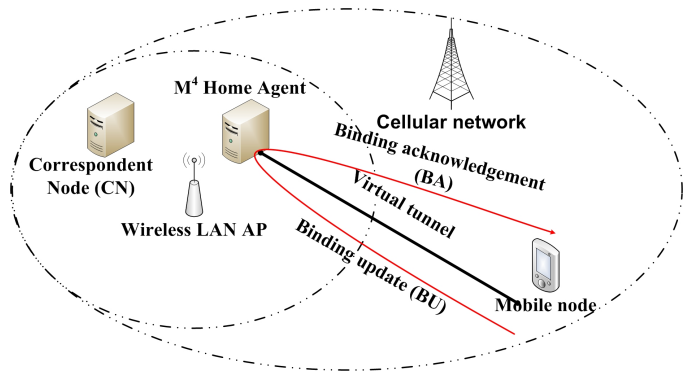

Fig. 1: MN calculates one-way (OWD) or round-trip time (RTT) delay using BU and BA packets. These delay values are then used by HMM for QoE estimation and prediction.
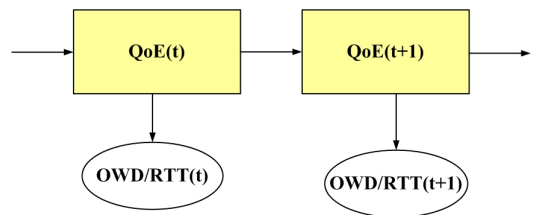

Fig. 2: HMM for QoE estimation and prediction.

Fig. 1 shows our method to QoE estimation and prediction using HMMs and M-MIP. A MN periodically exchanges BU and BA packets with the home agent (HA) or the correspondent node (CN). For each BU packet sent by the MN to HA/CN, a corresponding BA packet is sent from HA/CN to MN. The time difference between sending a BA packet from HA/CN to its reception at the MN is the OWD. The time difference between sending a BU packet from a MN and receiving a corresponding BA packet from HA/CN is the RTT delay. RTT delay estimation does not require clock synchronization between MN and HA/CN, compared to using OWD. The OWD or RTT delay is estimated at the network layer of MN. The HMM takes this OWD/RTT value as an observation and estimates or predicts the corresponding QoE state at the application layer. This problem is not trivial as HMMs need to discover, estimate and predict the hidden QoE states from underlying time-varying network conditions.

A. Analytical Model

We consider discrete-time HMMs [11] for QoE estimation and prediction in HAN. HMMs are temporal probabilistic models in which a system state, in our case QoE state is described by single discrete random variable. Fig. 2 shows our HMM for QoE estimation and prediction.

System states: We use the notation $S^t_{QoE_n}$ to represent the state of the QoE at time $t \in T$. At a given t, our system can be in any state $n \in N$. For example, $N = |5|$. Thus, the state space can be written as $\{S^t_{QoE_1}, S^t_{QoE_2}, ..., S^t_{QoE_5}\}$. When a system is in a particular state $S^t_{QoE_n}$, it outputs an observation or evidence (E^t).

Observations: In our system, the evidence is the current *OWD/RTT value* which is modelled as a Gaussian distribution in the form of: $P(E^t|S^t) = \mathcal{N}[E^t; \mu, \sigma^2]$, where μ is the mean and σ^2 is the variance. To describe state evolution over time, a QoE state transition matrix (TM) is defined. In this paper, we consider a first-order Markov process i.e., the current state is dependent only on previous state. It is shown in [7], [15] that first-order Markov process is sufficient for modeling temporal characteristics of the network channel. Thus, TM is defined as: $P(S_{QoE}^t|S_{QoE}^{t-1})$. To start the process, an initial state distribution is defined. It is represented as $\pi = P(S_{QoE_n}^{t=0})$.

Learning model parameters: In HMMs, the problem of learning is that of learning the model parameters $\Theta:\{\mu, \sigma^2, \pi, TM\}$. We consider the use of expectation maximization (EM) algorithm to train our HMMs. In EM algorithm, there are two main steps: E-step which computes posteriors over the states and the M-step which adjusts the model parameters to maximize the likelihood of posteriors calculated in the E-step. It is an iterative process leading to a guaranteed increase in log-likelihood of the model $log(\Theta)$ until convergence.

State estimation and prediction: After learning the model parameters using EM, we consider the Viterbi algorithm [11] for QoE state estimation. Viterbi is a dynamic programming algorithm which finds the most likely state sequence. Our second task is to perform QoE state prediction. It is a task of computing posterior distribution over the future states, given evidence till now. It can be written as $P(S_{QoE}^t|E^{t-1}; t \in T)$. The state with highest probability is the predicted state. In this paper, we are interested in one-step QoE prediction.

IV. RESULTS VALIDATION

A. QoE estimation and prediction in WLAN using one-way delay (OWD)

1) Simulation Setup: In this section, we use our HMM based approach to estimate and predict QoE states based on passive one-way delay (OWD). The OWD was calculated at the MN using BA packets sent from the HA/CN to MN. We performed several simulation studies using OPNET™ network simulator and considered several cases such as wireless network congestion and wireless signal fading in IEEE 802.11b/g WLAN. For the sake of brevity, we discuss the results related to wireless network congestion in this paper. For the wireless network congestion scenario, we considered a MN, HA, CN and three additional wireless nodes (WNs). To saturate the IEEE 802.11b access point (AP), we set up WNs to generate background UDP traffic. The maximum achievable bit rate was approximately 5Mb/s after which the AP dropped all packets due to buffer overflow. A CN node generated an additional 5 UDP packets (to mimic probe packets similar to BA) per second to help the MN collect path delay and QoE statistics. The size of each BA packet was 24 bytes, generating 960 bps as the M-MIP overhead. We selected those values based on [3]. We also tried packet size of 48 bytes but achieved similar results. Once the network reached its steady state, the MN initiated a call to the CN and calculated QoE and OWD using the probe packets. From simulation studies, we concluded that in case of heavy UDP traffic, wireless network congestion occurred due to increased end-to-end delay which in turn caused MOS to vary. The average MOS for ITU-T G.711 codec was 2.06. For ITU-T G.729 codec, it was 2.41. The collected statistics were used to train the HMMs.

2) Numerical Analysis: It is important to understand that the flow of BU/BA is different than the VoIP application traffic flow. Thus, sometimes it might not be possible for the MN to estimate or predict QoE due to lost BU/BA messages even though QoE can be calculated using the application traffic itself. Initially, we considered 2 BU/BA packets per second. However, our model could not estimate the QoE states correctly on one second basis. This was due to missing delay values caused by BA packet losses at the AP. From further simulation studies, we concluded that 5 UDP packets per second are sufficient for QoE estimation and prediction even in case of high packet losses. Further, it might happen that BA packet arrives too late (RTT/OWD>1 sec). In that case, it is considered to be lost and QoE is estimated and predicted to be in state 1 (discussed later). This was achieved by assigning evidence E^t=1 sec. To estimate and predict the QoE, we collected data using 100 simulation runs and analysed results related to both ITU-T G.711 and ITU-T G.729 voice codecs. We randomly selected 10 files out of 100 for each codec to train the HMMs. Each file consisted of a 101 second time-series of OWD and corresponding QoE statistics. We considered BayesNet Toolbox for MATLAB [9] for model parameter learning using EM algorithm and state estimation using the Viterbi algorithm. We wrote our own MATLAB program to gather prediction results. We trained the HMM based on three states. State 1 corresponds to QoE values (based on [5]) less than 2. State 2 corresponds to QoE values greater than or equal to 2 and less than 3. Finally, state 3 corresponds to QoE values greater than or equal to 3. For the sake of brevity, table I shows the learnt model parameters for ITU-T G.711 voice codec in case of wireless network network congestion. The prior matrix (π) and the transition matrix (TM) were estimated as follows:

$$\pi_{WLAN(G711)}^{congestion} = \begin{bmatrix} 0.6000 & 0.2000 & 0.2000 \end{bmatrix},$$

$$TM_{WLAN(G711)}^{congestion} = \begin{bmatrix} 0.9279 & 0.0596 & 0.0125 \\ 0.2817 & 0.3803 & 0.3380 \\ 0.0400 & 0.2400 & 0.7200 \end{bmatrix}.$$

TABLE I: HMM parameters learnt for ITU-T G.711 codec in case of WLAN network congestion.

	State 1	State 2	State3
OWD mean (μ)	0.4580	0.1302	0.0462
OWD var (σ^2)	0.0576	0.0010	0.0006

One of the best approaches for evaluating estimation and prediction accuracy is to perform cross-validation [13]. In cross-validation, some fraction of the data is kept for training and the remaining data is used as the test data. The training data and the test data are randomly chosen for each fold.
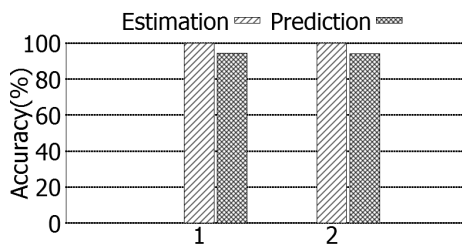
Fig. 3: Estimation and prediction accuracy of HMM in case of WLAN congestion. 1.) ITU-T G.711 codec. 2.) ITU-T G.729 codec.

TABLE II: HMM parameters learnt for ITU-T G.729 codec in case of heterogeneous access networks.

a. WLAN network interface.

	State 1	State 3
RTT mean (μ)	0.9905	0.0519
RTT var (σ^2)	0.0044	0.0079

b. CDMA 2000 network interface.

	State 1	State 2	State3
RTT mean (μ)	0.9519	0.6401	0.2857
RTT var (σ^2)	0.0055	0.0076	0.0025

For model validation, we considered 2- and 10-fold cross-validation.

We used Viterbi algorithm for QoE state estimation. From the learnt transition matrix ($TM_{WLAN(G711)}^{congestion}$), we gather that if the network path is congested (QoE is in state 1) or is not congested (QoE in state 3), it is more likely that the network path quality will remain the same for some time. If the QoE is in state 2, it is likely that it will fluctuate between state 1 and state 3. Fig 3. shows the estimation accuracy of HMMs in case of WLAN network congestion for both codecs using 2-fold cross-validation. We conclude that HMMs are able to accurately estimate with 100% accuracy the time-varying QoE in case of severe network congestion. We achieved similar results with 10-fold cross validation. We also checked the models prediction accuracy. Fig 3. shows the models prediction accuracy in case of WLAN congestion for both codecs. The results clearly validate that HMMs can accurately predict QoE in severe network congestion. The prediction accuracy was 94% approximately. Fig 4. shows an example of how HMMs can predict QoE states in complex network conditions such as WLAN network congestion.

B. QoE estimation and prediction using experimental data set and RTT delay

In this section, we use BA/BU pairs of the M-MIP [1] for passive RTT measurements. These RTT measurements were used by HMMs to estimate and predict the QoE.

1) Experimental Setup: For results validation, we obtained an experimental data set from the authors in [4]. This data set contains 12 different time series of RTT delay values for both WLAN and CDMA 2000 network interfaces corresponding to 12 different experimental runs. These experiments were conducted to understand the effects of roaming and handoffs on VoIP applications. The RTT values were calculated at 1 second time interval. Note that the ITU-T E-Model [5] considers OWD values to estimate MOS. Therefore, in this data set, we used the RTT measurements and divided them by 2 to derive the corresponding QoE values. We then used the RTT and QoE values to train the HMMs. The trained HMMs were used to estimate and predict the QoE. As mentioned previously, the parameters for HMMs were learnt using the EM algorithm in MATLAB. The model validation was done based on 2-fold cross validation.

2) Experimental Analysis: We considered 2 or a 3-state HMMs for QoE estimation and prediction. State 1 corresponds to QoE values less than 2. State 2 corresponds to QoE values greater than or equal to 2 and less than 4. Finally, state 3 corresponds to QoE values greater than or equal to 4. In case of WLAN, our HMMs sufficiently learnt using only two states, i.e., using state 1 and state 3. There were very few state 2 values and we folded them to state 3. This did not lead to estimation errors and loss of prediction accuracy. In case of CDMA 2000, there was sufficient data related to all three states which was used for learning the model parameters. Table II shows the learnt model parameters for ITU-T G.729 voice codec in case of WLAN and CDMA 2000 network interfaces. The estimated transition matrix and prior are as follows:

$$\pi_{WLAN}^{G729} = \begin{bmatrix} 0 & 1 \end{bmatrix}, \quad TM_{WLAN}^{G729} = \begin{bmatrix} 0.9500 & 0.0500 \\ 0.0654 & 0.9346 \end{bmatrix}$$

$$\pi_{CDMA2000}^{G729} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix},$$

$$TM_{CDMA2000}^{G729} = \begin{bmatrix} 0.7852 & 0.1333 & 0.0815 \\ 0.1111 & 0.8148 & 0.0741 \\ 0.0696 & 0.0435 & 0.8870 \end{bmatrix}.$$

From the learnt model parameters in case of WLAN, we gather once the QoE is in state 1 or in 3, it remains stable with probabilities greater than 90%. This suggests that WLAN either provides excellent QoE (state 3) or performs poorly (state 1). The poor performance was attributed to the MN moving out of the coverage area of WLAN and connecting to CDMA2000 network interface. In case of CDMA2000 network interface, once the QoE is in a particular state, it is likely that it will not fluctuate much. However, in case of the ITU-T G.711 voice codec, if the QoE is in state 2, there is a high probability that it might switch to either state 1 or 3 (results not shown due to lack of space). Multi-homed systems necessitate accurate QoE estimation and prediction on all network interfaces simultaneously [8],[16]. Fig 5. shows the estimation accuracy of HMMs for both network interfaces and codec. We concluded that HMMs provide excellent estimation accuracy of 100%. In case of mobility management protocols, HMMs can be used efficiently QoE estimation using passive probing.

Using the learnt model parameters (shown above), we performed analysis of the prediction capability of the proposed model. In case of QoE learning and prediction, HMMs keep in memory previously estimated QoE and RTT statistics to
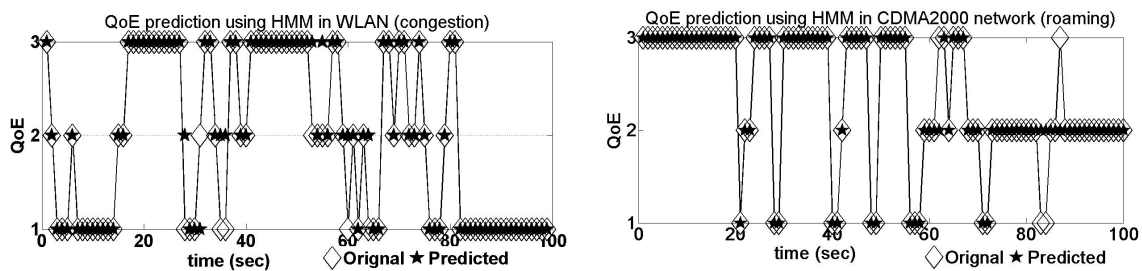
Fig. 4: Figure showing HMM and MIP-based method can accurately predict QoE under several time-varying conditions HAN.
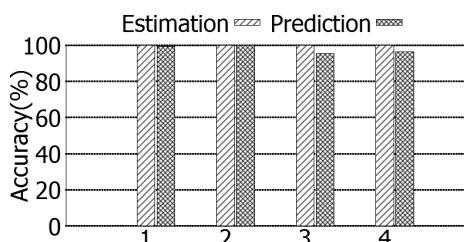

Fig. 5: Estimation and prediction accuracy using HMMs for WLAN and CDMA2000 network interfaces using experimental data set. 1.) WLAN with ITU-T G.711 codec. 2.) WLAN with ITU-T G.729 codec. 3.) CDMA2000 with ITU-T G.711 codec. 4.) CDMA2000 with ITU-T G.729 codec.

predict QoE states. In our experiments, HMMs kept in memory the statistics related to previous experiments to predict current QoE states. In particular, after driving a car with M-MIP [1] enabled MN for five times, the collected data was used to train the HMMs. The trained HMMs were then used to predict the QoE for the next five experimental runs. Fig. 4 shows the capability of HMM for QoE estimation and on-line prediction for CDMA 2000 network interface. Fig 5. shows the prediction accuracy of the proposed method for two voice codecs and for both WLAN and CDMA2000 network interfaces. The average prediction accuracy was 97.77%. From experimental analysis, we conclude that HMMs can model complex time-series pertaining to QoE in realistic network settings and are extremely beneficial for accurate QoE prediction.

V. CONCLUSION

This paper proposed, developed and validated a novel method for QoE estimation and prediction using HMMs and M-MIP based passive probing mechanism. Our results based on extensive simulation and experimental studies validate that HMMs trained using OWD or RTT delay calculated using BU and BA packets are suitable to accurately estimate and predict QoE for VoIP applications. Our method achieves absolute accuracy of 100% for QoE estimation and achieves accuracy of 97% for QoE prediction. To the best of our knowledge, ours is the first method to integrate QoE estimation and prediction capabilities directly into a mobility management protocol. The proposed method will facilitate the development of efficient algorithms for QoE-aware handoffs that require accurate QoE

estimation and prediction.

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