(DPMLA)-Weighted Dynamic Characteristics and Predictable Movement Learning Algorithm to Improve video Streaming in Heterogeneous Environments

Niall Maher, Shane Banks, Enda Fallon.

Software Research Institute,
Athlone Institute of Technology,
Dublin Road, Athlone, Co Westmeath.
Email: niallmaher@research.ait.ie, sbanks@ait.ie, efallon@ait.ie

***Abstract*— Mobile video is a key driver in the growth of mobile data. In heterogeneous networking environments, multimedia sessions are particularly vulnerable to varying network capabilities of underlying networks. This paper proposes a weighted dynamic and predictable based learning algorithm to improve video streaming in heterogeneous network environments (DPMLA). Current handover methods for seamless video streaming are performance limited as they do not consider how predictability movement can be used to alter the network handover decision. Research has shown that 93% of human movement is predictable. Studies also suggest that end user movement can be reliably predicted using mobile telecom services. The DPMLA algorithm considers both the dynamic performance of the network (Received Signal Strength (RSS), delay, loss) with a measure of the predictability of end user movement. Results illustrate that the DPMLA algorithm optimizes network selection and improves overall video streaming performance.**

Keywords—Mobility; Predictable; Predictable movement; MOS; Evalvid.

I. INTRODUCTION

Video streaming on a mobile device is becoming increasingly popular and is the key driver in the growth of mobile data. Mobile data makes up a significant percentage of total internet traffic. With the increasing adoption of mobile devices using video data, there will be an increasing demand for better Quality of Service (QoS). Cisco predicts that 75% or more of the traffic on mobile data will be generated by video streaming by 2019 [1].

As a real time application, multimedia sessions are particularly vulnerable to varying network capabilities of underlying networks. If a network handover from a high capacity Wireless LAN (WLAN) to lower capacity mobile network is not carefully managed, media session performance can be significantly degraded. To allow the user to experience the best possible Quality of Experience (QoE), mobile devices will have to move across (handover) different technologies to maintain seamless connectivity over large geographical areas. This handover can be initiated by the mobile device or the mobile cell for different reasons such as: bandwidth, round trip delay, packet loss, network lifetime, power consumption etc. Another factor that could be considered when determining handover is the movement of the mobile user throughout the heterogeneous network. The mobile devices will be able to maintain an active connection by using handover management while roaming through the heterogeneous network environment.

In order to deal with such variations of the handover process effectively, we are proposing an algorithm DPMLA which takes into account the traditional dynamic metrics along with the predictable movement of the end user. In [2], it was illustrated that 93% of human movement is predictable regardless of the distances people travel. The 93% predictability remains true both for those who travel far distances on a regular basis and for those who typically stay close to home. [3] has illustrated that end user movement can be predicted using mobile telecom services. Areas where predicted movement is easily established would be vehicles on motorways, public service vehicles where they operate in preconfigured routes, which are repeated at routine intervals. The instance of predictable movement investigated for this work was the movement of students in an educational institution based on class schedules.

This work investigates if the consideration of predictability of movement, along with dynamic performance characteristics, could improve handover decision management for video streaming. Dynamic performance characteristics are evaluated and an activation value is generated for each candidate Access Point (AP). Using an internal probability nodal tree, candidate APs are also graded on the probability that a mobile user will travel towards or away from their coverage. These weights applied to both the dynamic performance characteristics and the probability characteristics will learn every time a handover decision is made to or from the same network. This work evaluates a range of relative weightings of dynamic performance and mobility predictability scores. Results demonstrates that using the proposed DPMLA algorithm improves video streaming within heterogeneous environments as seen in the results section.

This paper is organized as follows: Section 2 outlines the related work in the area of video streaming quality metrics and ways to ensure good performance. Section 3 provides a brief overview of the technologies relevant to the work presented. Section 4 describes the experimental set-up used and presents results. Conclusions and future work is presented in Section 5.

II. Related Work

Video streaming has become a very topical area of research. In recent years there has been huge increase in the number of mobile devices with significant advances in the technology running on these devices. Video streaming uses the Real Time Control Protocol (RTCP). The protocol is derived from Real Time Protocol (RTP) and was defined in Request for Comments (RFC) 3550. RTCP is based on the periodic transmission of the control packets to all participants in the session using the same distribution mechanism as data packets [4].

Mobile Internet Protocol (Mipv6) [5] was defined by RFC3775 in June 2004. This allows a mobile node to transparently maintain connections while moving from one subnet to another without changing the mobile node home address. This functionally allows packets to be sent throughout the network regardless of the location in the network. Mipv6 allocates static Internet Protocol (IP) addresses for mobile nodes and allows mobile devices to act as servers. When connecting through a foreign network, a mobile device sends its location information to a home agent, which intercepts packets intended for the device and tunnels them to the current location.

A fuzzy based handover decision engine is proposed in [6], which looks at QoS and the data rate requirements of video streaming. This work explains how using the fuzzy based handover improves the overall network selection performance for a number of video streaming options by matching each stream to one of the available video streaming standards.

Paper [7] proposed an improvement in session handover in mobile wireless networks by using session rate prediction to enable video session continuity without the video freezing while using wireless mobile networks. The author tested this using an InterDomain and an IntraDomain by having a different number of sessions and workloads. The results presented in this paper suggests that the proposal saves workload on the server, which reduces latency and promotes smooth video streaming while mobile.

The experiments described in [8] shows that implementing high quality streaming of multimedia may result in a dramatic decrease in the battery power of a device, particularly smartphones.

Another researcher [9] has suggested a solution for video streaming for roaming clients that is able to compensate for the effects of oscillating bandwidth through predicting bandwidth and video quality. The researcher does this by combining an adaptive segmented Hypertext Transfer Protocol (HTTP) streaming system with an application framework for creating transparent multi-link applications, and a location-based QoS information system containing Global Positioning System (GPS) coordinates.

In [10] the researcher looks at video streaming services taking into consideration user preference for video content. This paper examines the different types of video content and evaluates if a different level of quality is needed for different content. For example, if the user was streaming the news perfect video quality would not be necessary, whereas if the user was streaming a full movie they would prefer near perfect quality. This research was tested by adding users' profiles and storing them on the video server. A new function Preference Factor (PF) was defined to hold the users' video preference which was used during the testing phase. An enhanced video streaming algorithm was defined and the results of the performance evaluation demonstrated that PF improves the overall experience and video quality.

III. Proposed Approach

This section provides a detailed description of the DPMLA algorithm. This work looks at applying relative weights to predictability movement and dynamic performance which will be taken into account for the network handover management to propose a candidate network selection. The following is Pseudo Code for the DPMLA algorithm

```
    Dynamic Subcomponent
        Collect Dynamic Data(RSS, delay, and loss)
        Normalise the metrics (1- poor, 100-excellent)
If (data == video)
        Give delay & loss a higher weighting
Assign weight to the metrics
Calculate the Dynamic Performance Score
        Assign network with scores
        Propose heights network score for handover.
Movement Predictability Sub Component
Collect GPS Data (From user location)
Build a Nodal Tree Based on all Available Networks
Populate Tree with Historical Data of predicted movements
Determine Probability of Movement in all available Direction
        Propose node with Highest Probability Score as Network
Handover Choice
Path Assessment Component
If (Dynamic Network Selection == Movement Predictability Selection
Network)
        Perform Handover
        Else
If (Dynamic Network Selection != Predictability Movement Network
Selection)
Weigh the previous performance of each selection
        If (Dynamic Network > Predictability Movement)
Perform Handover = Dynamic Network Selection
Else    Perform Handover = Predictability Movement Network
Selection
Supervised Learning
If (Perform Handover = Dynamic Network Selection)
Adjust Dynamic weight allocation = Correction Value
Adjust Nodal Tree Based on Users Movement
```

Fig. 1. Pseudocode for the DPMLA algorithm.

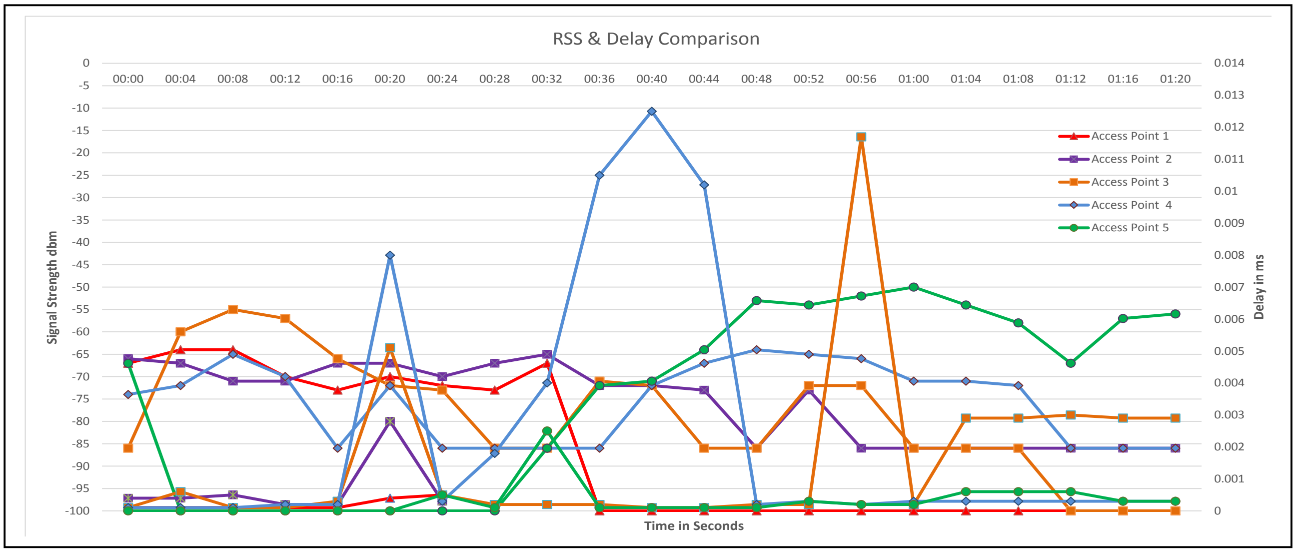

Fig. 2. RSS and Delay Comparison

DPMLA takes an input of dynamic network performance metrics, for this experiment the metrics were RSS, delay, and loss. DPMLA can be adjusted to take more input metrics if needed. After being inputted into the algorithm these metrics are normalised on a scale of 1 (poor) to 100 (excellent). Following the metrics being normalised, they are assigned dynamic weights reflecting the importance of those metrics to the overall network performance. For example, in video streaming we would expect that delay and loss would get a higher dynamic weighting than RSS. The dynamic performance score is then generated by multiplying the normalised values by the dynamic weights allocated and summing them together to reveal the dynamic network performance activation value of all available networks. The highest activation value will be proposed as the dynamic path selection.

To evaluate the predictability of movement approach of the DPMLA algorithm, the algorithm determines the current location of the user using the GPS module on the users' device. DPMLA than creates a nodal structure tree to represent all available networks in local proximity to the end user. The nodal structure tree is then populated based on historical mobility data recorded on the end users device. Using this data, DPMLA allocates the probability of the user moving in the direction of each network. The node with the highest score is suggested by the probability assessment module as the candidate network.

The DPMLA algorithm takes two path selections, one from dynamic performance and the other from the predicted movement assessment. Both path selections are passed into the path assessment section of the algorithm. If both dynamic and predicted movement path choices are the same, that path will be chosen for handover. But if both subcomponents select different paths, the DPMLA algorithm will weigh the previous performance of each selection when determining the current optimal path selection.

IV. RESULTS

Experiments were undertaken in AIT campus to investigate the performance of the DPMLA approach. These tests included an observational study, followed by a brute force test on the network. Following the brute force testing on the network, slope test will be carried out on the dynamic characteristics. Finally the slope test results will be weighed against predictability movement in order to improve video streaming

. The observational study generated a probability of students moving in different directions between classes and to determine which path each student would choose to get to their destination. After collecting the information from the observational study, a heterogeneous network was created using Linksys wireless broadband routers, which were placed in different locations between the start point and destination of the students. To collect the dynamic performance information of the network the route that the majority of the student took was physically walked crossing between different network cells over the course of the route. This allowed the recording of the RSS, delay and loss of each available network using network tools while walking the route. The network information was extracted and inputted into Network Simulator 3 (NS3) to create simulation models.

Figure 2 above displays the RSS and delay of all network within the HetNets topology. This data was collected throughout the experimental testing phase of this research. What can be seen from Figure 2 is the experiments setup has roughly equal signal strength and relative low delay on all available network. There are two situations where networks are unavailable within this experiment, these are at 4 seconds where AP 5 reads -100dbm and at 36 seconds where AP 1 reads -100dbm. What can also been seen from Figure 2 is a delay spike in certain areas of the experiment e.g. 16 and 36 seconds, the reason for these spikes is because over the route covered in the experiments the students entered a stairwell while traveling between floors within the college building.

This experimental setup is an ideal example of where setting dynamic thresholds or using the built in mobile handover approach could result in spurious handover causing downtime or even loss of connection. Using the DPMLA algorithm would avoid the potential spurious handover because it takes into account the dynamic performance along with the direction which the mobile user is moving. Therefore using predicted movement to influence the handover decision making process allows for seamless handover and optimisation of available network.

Table 1 Brute force tests carried out and resulting MOS scores.

		W1= 0	W1 = .25	W1 = .5	W1 = .75	W1 = 1
W 3 = 0	W2 = 0	2.76	3.05	3.05	3.05	3.03
	W2 = .25	2.75	3.04	3.04	3.03	3.05
	W2 = .5	2.76	3.24	3.03	3.04	3.03
	W2 = .75	2.75	2.83	3.08	3.03	3.03
	W2 = 1	2.76	2.83	2.76	2.83	2.76
W 3 = .25	W2 = 0	2.36	3.05	3.05	3.05	3.05
	W2 = .25	2.83	3.03	3.03	3.03	3.05
	W2 = .5	2.84	3.12	3.07	3.03	3.04
	W2 = .75	2.82	2.83	3.03	3.08	2.81
	W2 = 1	2.8	2.83	3.21	3.07	3.03
W 3 = .5	W2 = 0	2.36	3.13	3.05	3.05	3.05
	W2 = .25	2.8	2.92	3.17	3.04	3.05
	W2 = .5	2.82	3.12	3.03	3.03	2.83
	W2 = .75	2.84	2.83	3.03	3.08	3.03
	W2 = 1	2.83	2.83	3.12	3.03	3.08
W 3 = .75	W2 = 0	2.36	2.84	3.17	3.05	3.05
	W2 = .25	2.71	2.86	3.02	3.03	3.05
	W2 = .5	2.79	3.11	3.03	3.03	3.04
	W2 = .75	2.83	2.85	2.91	3.03	3.08
	W2 = 1	2.85	2.84	3.11	3.03	3.03
W 3 = 1	W2 = 0	2.36	2.56	3.11	3.17	3.05
	W2 = .25	2.46	2.83	3	2.96	3.02
	W2 = .5	2.77	3.02	2.89	2.98	3.15
	W2 = .75	2.76	2.8	2.88	3	3
	W2 = 1	2.83	2.81	3.08	3	3.05

Table 1 is a brute force test of all dynamic characteristics (DC) W1= Loss, W2 = Delay and W3 = RSS all increasing in a .25 increments. What table 1 illustrates is as the weighting loss increases MOS increases meaning there is a correlation between weight allocated to loss and the MOS score.

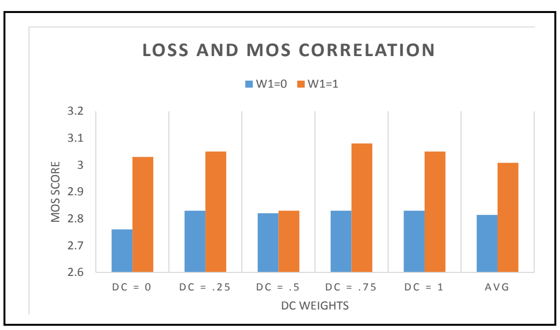

Fig. 3. Loss and MOS Correlation

Figure 3 illustrate the MOS score correlation with Loss, what we can see from the graph is there is only slight change in MOS as the DC are increased. Where when Loss is equal to 1 MOS gets a significant increase.

Figure 4 and 5 graphically illustrate the effects of weights alteration on MOS score from table 1. The following are broken down based on Weight 3 (RSS).

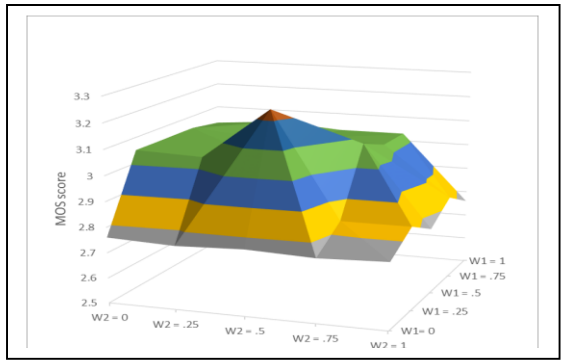

Fig. 4. Represents the MOS score when W3 = 0

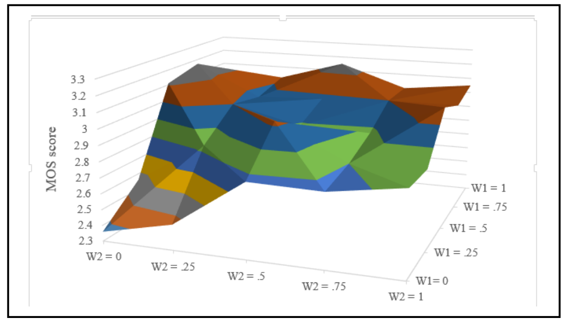

Fig. 5. Represents the MOS score when W3 = 1

Table 1 can be broken down into four groups: optimal, Very good, Good, Fair. Based on MOS scores.

Optimal simulation performance weights				
Test No:	Loss	Delay	RSS	MOS Score
11	0.25	0.5	0	3.24
22	0.5	1	0	3.24
47	0.5	1	0.25	3.21

Table 2. Optimal weight configuration

Table 2 illustrates the optimal dynamic weight configurations possible for the network topology. In this configuration we see that the experiments result in a high MOS score, when there is a low weight allocated to RSS and an equal weight allocated to delay and loss. Based on this RSS should be given a low weight allocation within the algorithm, and delay a higher weighting.

Fair simulation performance weights				
Test No:	Loss	Delay	RSS	MOS Score
25	0	0	0.25	2.36
50	0	0	0.5	2.36
75	0	0	0.75	2.36

Table 3. Fair weight configuration

Table 3 shows the tests that only resulted in a fair MOS score. These were tests that only took an RSS input, and which resulted in MOS score in the low 2's.

W1 (Loss)	W2 (Delay)	W3 (RSS)	Threshold	Iterations	MOS	Slope	Correction	Learning Rate
0.15	0.1	0.05	1	1	2.53	2.53	0.253	0.1
0.403	0.353	0.303	1	2	2.52	1.26	0.126	0.1
0.4857	0.479	0.429	1	3	2.76	0.827	0.0827	0.1
0.6117	0.605	0.555	1	4	2.86	0.595	Random	0.1
0.3117	0.705	0.555	1	5	2.78	0.084	0.0084	0.1
0.3201	0.7134	0.5634	1	6	2.77	0.052	0.0052	0.1
0.3253	0.7186	0.5686	1	7	2.77	-0.007	-0.0007	0.1
0.5253	0.4186	0.4686	1	8	2.75	-0.023	-0.0023	0.1
0.523	0.4163	0.4663	1	9	2.75	-0.008	Random	0.1
0.5222	0.4155	0.4655	1	10	2.75	-0.006	-0.0006	0.1
0.6222	0.6155	0.5655	1	11	3.13	0.072	0.0072	0.1
0.6294	0.6227	0.5727	1	12	2.87	0.062	0.0062	0.1
0.6356	0.6289	0.5789	1	13	2.9	0.042	0.0042	0.1
0.7356	0.8289	0.3789	1	14	2.91	0.009	Random	0.1
0.7316	0.8298	0.3798	1	15	2.91	-0.04	-0.004	0.1
0.7325	0.8307	0.3807	1	16	2.91	0.009	0.0009	0.1
0.7334	0.8316	0.3816	1	17	2.91	0.002	0.0002	0.1

Fig. 6. Slope learning phase tests

Figure 6 illustrates the random weight adjustment and the slope of the regression line formula. Figure 6 shows that every 5 cycles a random value was added to the weights to avoid reaching a local maximum while in the learning phase of the algorithm.

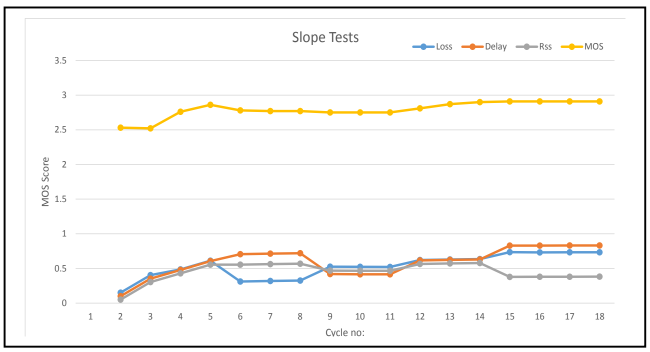

Fig. 7. Slope Test Results

Figure 7 is the results generated from the training phase of the DPMLA algorithm and a graphical representation of Figure 6. In the training phase the weights are trained as the algorithm cycles through different weight configurations. The algorithm uses a slope of the regression line formula to train the Artificial Neural Networks (ANN). This works by adding the cycle number and MOS score to the formula. The formula keeps running each time, adding the correction value to the weights and generating a new MOS and slope value until the slope reaches a value of 0. When the slope has reached 0 or an absolute 0 the training phase is complete. In figure 7, the training phase takes 18 cycles to complete. After the training was completed the execution value can then be used for test purposes.

Tests were carried out with different weight configurations on the two subcomponents using the trained value. The results from these test can be seen in Table 4.

Test No:	DC	Predicted Movement	MOS
1	3	0	2.9
2	1.5	1	3
3	1	1	2.8

Table 4 Evaluation of weight configuration on trained ANN values.

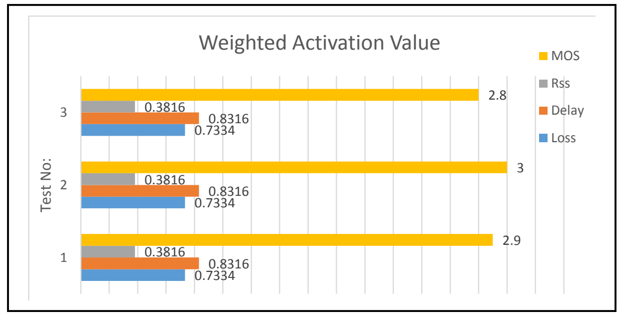

Fig. 8. Weighted Activation Values

Figure 8 shows the different configurations for the testing of different weights on the dynamic and predicted movement. These weights were applied to the dynamic activation values and the predicted movement activation values and would only come into consideration if both subcomponents had chosen different access points to connect to.

V. Conclusion

This paper proposes a weighted dynamic and predictable based learning algorithm to improve video streaming in heterogeneous network environments (DPMLA). Current handover methods for seamless video streaming are performance limited as they do not consider how predictability movement can be used to alter the network handover decision. Results illustrate that taking predicted movement into account in the decision making process at a 2:1 weighting on dynamic performance over predicted movement resulted in the highest MOS score over the transmission of video over the network. What was also proven is, without a predicted movement input into the decision making process, the results were only of fair quality. This proves that predicted movement could be used in certain areas to improve QoE and seamless video streaming.

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