Towards Personalised and Adaptive Multimedia in M-learning Systems

Arghir-Nicolae Moldovan and Cristina Hava Muntean
School of Computing
National College of Ireland
Mayor Street, IFSC, Dublin 1, Ireland
amoldovan@student.ncirl.ie, cmuntean@ncirl.ie

Abstract: Apart being one of the key factors driving m-learning acceptance, the new generations of powerful and affordable devices also contribute to a fast increase in educational multimedia content consumption. Multimedia content has many benefits for m-learning, but it also poses a number of challenges regarding the content delivery to a multitude of mobile devices with various characteristics over wireless networks with different performance. This paper proposes a solution for enabling multimedia content personalisation based on learner's device screen resolution, as well as multimedia content adaptation based on the available network bandwidth. Video profiles consisting of recommended encoding parameters are associated to different classes of device screen resolutions, and an automatic mechanism is deployed for selecting low bitrate values for bandwidth driven adaptation. Results from a subjective study have shown that despite these values were below the minimum recommended values, they offer a good user perceived quality.

Introduction

Mobile devices such as smartphones, tablets and netbooks are fast becoming the primary means of accessing the Internet. Driven by the fast increase in mobile device sales, mobile Internet not only that grows significantly faster, but this is expected to become ten times bigger than desktop Internet in terms of device numbers (Meeker 2009). The fact is further indicated by various forecasts, that estimate yearly global shipments of smartphones and tablets alone to be close to 850 million (In Stat 2011), and more than 100 million (Abi Research 2011) respectively, by 2015.

As mobile devices have improved significantly in terms of features and capabilities, they are increasingly used for accessing m-learning applications. Latest embedded devices come with larger and crisper screens, high-speed wireless connectivity and faster processors, enabling learners' access to rich educational multimedia content anytime and anywhere. At the same time, educators can create more engaging, interactive and multimedia rich m-learning applications in order to enhance learners' experience and their satisfaction, key factors contributing to the acceptance of m-learning systems (Liaw et al. 2010).

In particular, video content production and consumption for educational purposes has seen a fast growth and is expected to accelerate over the coming years (Kaufmann & Mohan 2009). Educational multimedia clips offer a rich display of information and can help learners understand difficult concepts, while real-time multimedia streaming enables face-to-face-like experiences in online learning environments. However, high-quality multimedia requires significant network bandwidth and device resources in order to be properly retrieved and displayed by the learner device. Learners may have mobile devices with different characteristics (e.g. screen size, CPU power), and multimedia playback capabilities, which have to be considered for encoding the educational multimedia content at an optimum quality level. Moreover, during its delivery the quality of the multimedia clip can be significantly affected by a low or variable network bandwidth. Therefore, each mobile learner needs to be provided with multimedia educational content encoded with appropriate parameters and quality level, so that it can be displayed properly by his/her mobile device, and can be delivered over the available wireless network. To achieve this, mechanisms for personalising the multimedia content based on learner's device characteristics and for adapting the content to the available network conditions need to be integrated with m-learning systems.

This paper extends the significant body of research that addressed educational content personalisation and adaptation in e-learning generally and m-learning particularly, by proposing a solution for enabling educational multimedia content personalisation and adaptation in m-learning systems. Personalisation based on learner device screen resolution and adaptation based on the available network bandwidth are particularly addressed. To overcome the multitude of device screen resolutions, learners' devices are grouped in different classes, and video profiles consisting of recommended encoding settings are associated to each class. While intervals of recommended values for streaming educational multimedia clips are provided, selecting specific values for encoding particular clips is especially difficult. This is because both content related factors such as the clip dynamicity, and network transmission conditions, have to be considered in order to provide learners with a good quality level. Content specific bitrate-selection is enabled with the help of an automatic mechanism that uses objective video quality assessment metrics to estimate learner perceived quality of the multimedia clips. A subjective study was conducted using educational multimedia clips with different characteristics. The results presented in this paper have shown that the bitrate values selected using the automatic mechanism offer a good enough quality level for enabling knowledge acquisition from the multimedia clips.

The rest of the paper is organised as follows. Next section presents research background related to this paper. Following, the proposed solution for enabling multimedia content personalisation and adaptation in m-learning systems is described. The subjective study methodology and results are presented after that, while in the end conclusions are drawn.

Research Background

To support learners' access to educational content anytime and anywhere, m-learning has to overcome a number of issues and challenges that are mainly related with the learners (e.g. their needs, preferences, location, etc.), as well as with the variety of mobile device characteristics. To overcome these challenges, personalisation and adaptation have gradually been brought to the forefront of the research in the area of m-learning in particular and e-learning in general. Educational content personalisation and adaptation may be learner oriented or device oriented.

Approaches for *learner oriented* personalisation have mainly concentrated on delivering personalised educational content tailored to individual learners or groups based on their characteristics. Various learner characteristics were considered as important input in the personalisation process such as their needs, preferences, goals, knowledge level, skills or learning styles (De Bra et al. 2003; Brusilovsky & Millán 2007; Graf et al. 2009; Chang et al. 2009). Learners' location was also considered for personalising the educational content to the *learning context* (Yin et al. 2010).

Delivering learning content to mobile devices requires the m-learning applications to be able to run efficiently on a multitude of mobile devices with different characteristics (e.g. device screen and its resolution, CPU speed, memory capacity, I/O interfaces (e.g. touch screen, keyboard), wireless connectivity (e.g. WiFi, 3G)), different operating systems, as well as different features and capabilities (e.g. web-browser performance, audio/video formats supported, Flash/Java support, etc.).

The majority of the *device oriented* personalisation and adaptation solutions have mainly focused on the mobile device screen resolution. Various frameworks for creating device independent user interfaces were proposed (Ally et al. 2005; Zhao & Okamoto 2008), which separate the learner interface from the educational content and use a device independent language such as XML to describe the interface. The user interface is then automatically generated, based on the mobile device characteristics. *Device connectivity* related factors such as the available network bandwidth, were also addressed in the educational content adaptation (Muntean 2008). Most of the research addressing learner device oriented personalisation and adaptation of educational content, has focused on adapting the content presentation, where the content is represented by various pieces of information such as text, images, audio and/or video clips.

Educational multimedia content personalisation and adaptation in particular, may also be driven by learner characteristics and the learning context, as well as by the device characteristics and network related factors (Muntean C.H. & Muntean 2009). Device characteristics such as processing power, screen resolution (Kim & Yoon 2009) and the battery life (Moldovan & Muntean 2009), as well as the available wireless network bandwidth (Muntean V.H. & Muntean 2009), have been addressed.

Multimedia content personalisation usually is done a single time before the content delivery. This consists in providing a learner with educational material that better fits his/her needs, or with a version of the same multimedia content encoded in a way that meets the device and network constraints. Encoding parameters that can be changed include the compression format, resolution, bitrate and frame-rate, while the versions can be created off-line or on-line using real time transcoding.

Additionally, multimedia content adaptation involves changing the content characteristics during its delivery, to overcome factors such as, e.g. the variable network bandwidth. This can be done by switching between several versions of the same clip created off-line (Zambelli 2009), by re-encoding the clip in real-time or by using a scalable video codec (Schwarz et al. 2007).

Enabling Educational Multimedia Content Personalization and Adaptation

This section presents the proposed solution for enabling multimedia content personalisation based on learner device screen resolution, and multimedia content adaptation based on the available network bandwidth. Various types of mobile devices that are most suitable for m-learning are presented first.

M-learning Devices

Currently there are a multitude of mobile devices that can be used for m-learning. These so called *"m-learning devices"* (Quinn 2008), differ broadly in terms of characteristics such as device size and its form-factor, screen size and its resolution, wireless/cellular connectivity type and speed, CPU speed, memory capacity, I/O components, etc.

Although *Feature Phones* with Web connectivity and *Laptops* can be used for m-learning, they either have poor performance and limited functionality (feature phones), or they are too bulky and have poor battery life for enabling true mobility (laptops). As opposed, *Smartphones* and *Ultra Mobile Devices (UMDs)* (see Figure 1), not only have more advanced web-browsing and multimedia capabilities than feature phones, but they also are more compact and lightweight, and often have better battery life than laptops. UMDs cover a multitude of mobile devices such as Mobile Internet Devices (MIDs), Tablets, Ultra Mobile PCs (UMPC), Netbooks, Smartbooks, etc.

Apart of smartphones and UMDs other devices with wireless connectivity but more dedicated functionalities such as *Portable Media Players (PMPs)*, *Handheld Game Consoles (HGCs)* or *e-readers* can also be used for m-learning. However such devices may be expected to decrease in popularity as mobile users increasingly rely on their capable smartphones or tablets to perform more and more activities, from browsing the Internet, to watching videos and listening music, playing games, reading e-books, etc.

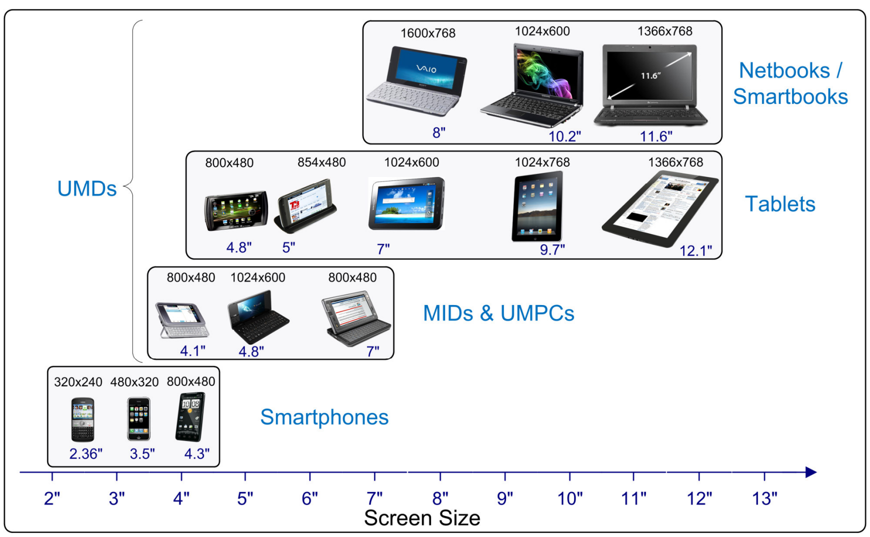


Figure 1: Common form-factors, screen sizes and screen resolutions of the latest m-learning devices

Looking at the screen size and form-factor (see Figure 1), one can note the similarities and the differences between the various types of m-learning devices. Smartphones usually are more compact, may present a physical keyboard and/or a touch-screen, and as of 2011 may have a screen size as large as 4.5" [1] in the touch-screen variant. UMDs as opposed come in a significant higher variation of form factors and may have a screen size as small as 4" or as large as 12". Figure 1 also shows that different m-learning devices with different screen sizes may present the same screen resolution. For example, a resolution of 1024x600 pixels can be seen in a 10.2" Netbook[2], a 7" tablet[3], as well as in a 4.8" UMPC[4].

---

[1] Samsung i997 Infuse 4G Specifications, http://www.gsmarena.com/samsung_i997_infuse_4g-3705.php
[2] Samsung NP-NC10 Specifications, http://www.umpcportal.com/products/Samsung/NC10/NP-NC10
[3] Samsung P1000 Galaxy Tab Specifications, http://www.gsmarena.com/samsung_p1000_galaxy_tab-3370.php
[4] Viliv N5 Specifications, http://www.umpcportal.com/products/Viliv/N5

Video Profiles for Classes of M-learning Devices

The multitude of screen resolutions with different aspect ratios used by m-learning devices, make difficult educational multimedia clips personalisation based on learners device screen resolution. Ideally, for optimum quality level each learner should receive a version of the multimedia clip adapted to fit its particular screen resolution. However, in practice this is not feasible due to the very high number of versions that would need to be created and stored for each multimedia clip.

A list of the most common m-learning devices screen resolutions, compiled using information from Cartoonized[5] and UMPC Portal[6], is presented in Table 1. To reduce the number of versions to be created, this paper proposes to group the m-learning devices in four different classes based on their screen resolution: *Large Screen Resolution Devices (LRD), Medium-Large Screen Resolution Devices (MLRD), Medium-Small Screen Resolution Devices* and *Small Screen Resolution Devices (SRD).*

Device Class	Video Profile	Display Resolution	Aspect Ratio	Standard Name	M-Learning Devices
LRD	720p	1600x768	25:12	UWXGA	Netbooks
		1366x768	16:9	WXGA	Netbooks, Tablets
		1280x800	16:10	WXGA	Netbooks, MIDs & UMPCs
		1280x768	5:3	WXGA	Netbooks
		1024x768	4:3	XGA	Netbooks, Tablets
MLRD	480p	1024x600	16:10	WSVGA	Netbooks, Tablets, MIDs
		1024x576	16:9	WSVGA	Netbooks
		1024x480		UWVGA	Smartphones, MIDs
		960x640	3:2	DVGA	Smartphones
		960x540	16:9	qHD	Smartphones
		960x480	2:1	UWVGA	Smartphones, MIDs
		854x480	16:9	FWVGA	Smartphones, MIDs
		800x600	4:3	SVGA	MIDs & UMPCs, Tablets
		800x480	5:3	WVGA	Smartphones, MIDs, Netbooks, Tablets
		640x480	4:3	VGA	Smartphones, PDAs,
MSRD	360p	640x360	16:9	nHD	Smartphones
		480x360	4:3	HVGA+	Smartphones
SRD	240p	480x320	3:2	HVGA	Smartphones, PMPs, MIDs
		480x272	16:9	HD1080/16	Smartphones, PMPs, HGCs
		432x240	9:5	WQVGA	Smartphones
		427x240	16:9	WQVGA	Smartphones
		320x240	4:3	QVGA	Smartphones, PMPs, PDAs, MIDs

Table 1: Common display resolutions for m-learning devices

A *video profile* consisting of a set of video encoding parameters (*video codec*, *reference resolution*, *bitrate* and *frame-rate*) is associated to each device class. As m-learning devices may have screen resolutions as low as 320x240 and as high as 1600x768, the 240p, 480p, 360p and 720p, video profiles are used. The video profile names indicate the vertical resolutions at which the educational multimedia clips are encoded.

Since the m-learning devices screen resolution, as well as the educational multimedia clips video resolutions may have different aspect ratios, both resolutions should be considered when selecting the profile for a particular learner device. For example a mobile device with a 640x480 resolution can easily accommodate the 480p profile (640x480 clip resolution) for an educational clip with a 4:3 aspect ratio, but only the 360p profile (640x360 clip resolution) for an educational clip with a 16:9 aspect ratio.

The 16:9 aspect ratio has become very popular in recent years, being widely adopted in HD cameras (720p and 1080p), television and displays. Moreover a large number of m-learning devices use wide screen resolutions such as nHD, WVGA or WXGA, that are more suitable to display educational clips with a 16:9 aspect ratio. Figure 2 illustrates the reference resolutions with an aspect ratio of 16:9, corresponding to the four video profiles. As indicated in the figure, the resolution basically doubles in size with every profile.

---

[5] Cell Phone Screen Resolution by Brand and Model, http://cartoonized.net/cellphone-screen-resolution.php
[6] Netbook, Tablet, UMPC and MID Comparison, http://www.umpcportal.com/products/

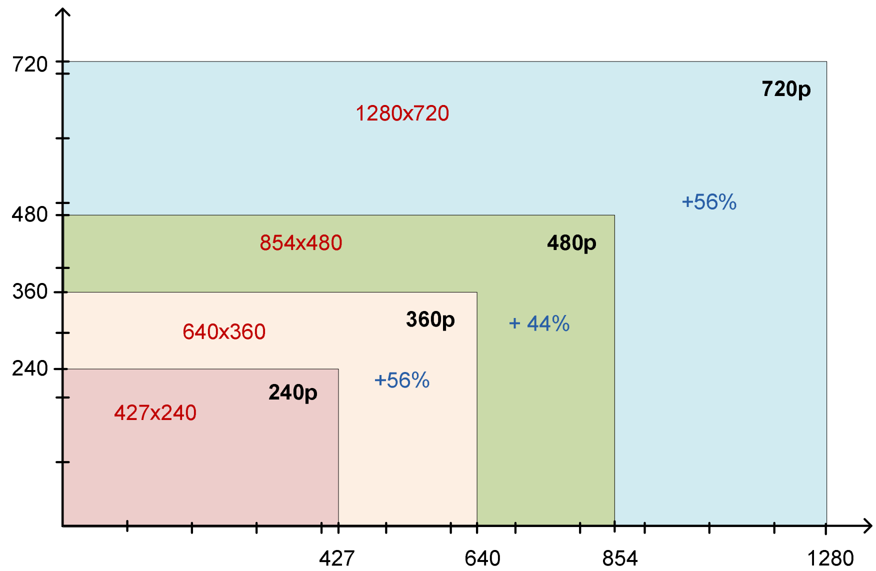


Figure 2: Reference resolutions for the four video profiles

For a particular video resolution and frame rate, the video bitrate of a compressed educational multimedia clip depends on the video codec being used, with some codecs offering better compression for similar quality level (e.g. bad, good or excellent). Furthermore, depending on the content characteristics (e.g. details, motion content, colours used, etc.), different educational clips may require different bitrates for the same quality level, with more complex and dynamic clips usually requiring a higher bitrate.

Various aspects need to be addressed when selecting the video codec and the bitrate for encoding educational multimedia clips. Examples include but are not limited to what video codec is supported by learner's device and/or application? The videos are intended for downloaded or for streaming? If they are streamed what is the available wireless network bandwidth?

Examples of popular video codecs are H.264/MPEG-4 AVC, Theora, VP8 and VC-1. H.264 is the latest version of the MPEG-4 video codec standard, providing approximately 50% bit rate saving as compared to the previous generation MPEG-4 Part 2, for the same quality level (Wiegand et al. 2003). Over the past years the format was increasingly adopted by Internet multimedia services such as IPTV, Video on Demand, video conferencing or video sharing (e.g. YouTube). Furthermore, an increasing number of mobile devices come with H.264 decoding capabilities.

Table 2 presents intervals of bitrate values corresponding to the four video profiles, which can be used for encoding H.264 educational multimedia clips for both local playback and streaming to m-learning devices over WiFi. The bitrate intervals are based on guidelines and recommendations for encoding H.264 multimedia content for local playback[7] and streaming[8,9], and correspond to standard video frame-rates such as 24fps, 25fps and 30fps.

Device Class	Video Profile	Video Codec	Resolution [pixels]	Local Playback Bitrate [Kbps]	Streaming Bitrate [Kbps]	Frame Rate [fps]
LRD	720p	H.264	1280x720	5000-6000	1500-2200	24-30
MLRD	480p		854x480	1000-2000	600-1000	
MSRD	360p		640x360	500-1000	350-550	
SRD	240p		427x240	300-500	150-300	

Table 2: Video profiles for classes of m-learning devices

[7] Creating Amazing Video Content with H.264, http://www.apple.com/mx/quicktime/tutorials/h264.html
[8] Dynamic streaming with FMS 3.5, http://www.adobe.com/devnet/flashmediaserver/articles/dynstream_on_demand.html
[9] Welcome Streaming Media Roundtable Discussion with Four Thought Leaders in the Industry, http://event.on24.com/event/28/89/58/rt/1/documents/slidepdf/stm_slides_1095.pdf

Selecting Specific Bitrate Values

When creating personalised educational multimedia clips for m-learning, specific bitrate values need to be selected in the recommended intervals for each video profile. While the high bitrates recommended for download clips enable excellent visual quality, it is not clearly mentioned and backed up by evidence what quality offer the recommended streaming bitrates. Since video quality is one of the main factors contributing to learners experience, it is important to select bitrate values that offer at least a good level of learner perceived quality. Moreover, when an educational multimedia clip is streamed to the learner device over the wireless network, its perceived quality may be significantly affected by transmission errors such as loss and delay, especially during real-time streaming (e.g. student watching a live lecture recording). In such situations, adapting the bitrate of the streamed clip for enabling a smooth viewing experience may result in a higher overall quality, than streaming the clip at a higher but fixed bitrate.

To enable educational multimedia content adaptation based on the network conditions, a bitrate value as small as possible that still offers a good learner perceived quality has to be detected for each video profile. An automatic mechanism, BitDetect, for detecting thresholds up to which the bitrate of a multimedia clip can be decreased while maintaining a good quality level, was proposed for the particular case of saving the mobile device battery life (Moldovan, Moraru, & Muntean 2011). BitDetect takes as input an excellent quality multimedia clip with a specific resolution and a high bitrate suitable for local playback, and returns a good quality version of the clip having the same resolution but a significantly lower bitrate that is suitable for streaming. This is done by gradually decreasing the video bitrate and estimating the quality of the resulting versions using objective video quality assessment metrics. Two objective metrics, the Peak Signal-to-Noise Ratio (PSNR) (Wang & Bovik 2009) and Structural Similarity Index (SSIM) (Wang et al. 2004) are used.

Although the mechanism was proposed for the particular context of battery power saving, this can be used as well for detecting good quality bitrate values for enabling the educational multimedia clips adaptation based on network conditions. Since different educational clips may have different characteristics (e.g. dynamicity, colours), they may require different bitrates for a good quality level. Therefore, the good quality bitrate value has to be detected individually for each multimedia educational clip and for each video profile. This process can be facilitated by integrating an automatic mechanism such as BitDetect with an adaptive m-learning system (Moldovan, Molnar & Muntean 2011).

Case Study and Experimental Results

A subjective study was conducted in order to assess if the specific bitrate values recommended by the BitDetect mechanism are suitable for multimedia-based m-learning. The goal of the study was twofold: (i) to assess how learners perceive the quality of different educational multimedia clips encoded at the recommended bitrate values, and (ii) to assess if the quality is good-enough so that learners can achieve knowledge from the clips. To assess the results consistency across different video profiles and educational multimedia clips, the study was conducted for two video profiles (360p and 480p) using eight educational multimedia clips with different content characteristics.

Educational Clips

Eight clips were selected from a list of 904 educational multimedia clips that were downloaded from iTunes U[10] and Miro Guide[11]. Eight categories of educational multimedia clips were identified during the selection process: *slideshows*, *interviews*, *lab demos*, *screencasts*, *graphics* (3d game and virtual world recordings), *presentations*, *documentaries*, and (computer generated) *animations*. Each multimedia clip that was selected corresponds to one of these categories. Representative frames for the eight clips are presented in Figure 3. More detailed descriptions of the multimedia clips can be found in (Moldovan, Molnar & Muntean 2011). The high quality original clips were H.264 compressed and had a resolution of 960x540 or 1280x720 pixels, a frame-rate of 24 fps or 30 fps, and a bitrate between 2 Mbps and 5 Mbps.

Two up to 30 seconds long test sequences were extracted from each educational clip. Eight of the sixteen sequences (Arts A, Dubus A, etc.), were re-encoded at the reference resolution corresponding to the first profile

[10] Apple iTunes U, http://www.apple.com/itunes/
[11] Miro Guide, http://www.miroguide.com/

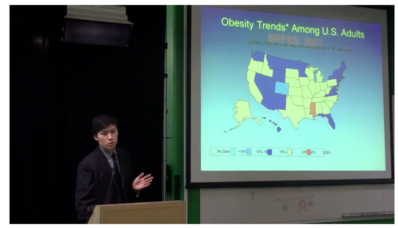

a) Arts (Slideshow)


b) Dubus (Interview)


c) Hotness (Lab Demo)

d) Hulu (Screencast)


e) Languagelab (Graphics)



f) Obesity (Presentation)

g) Sleep (Documentary)

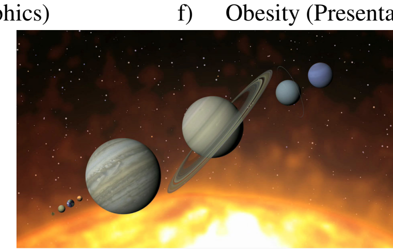

h) Sol (Animation)

Figure 3: Representative frames for the eight educational multimedia clips used for testing

tested, 360p, while the other eight sequences (Arts B, Dubus B, etc.) were re-encoded at the reference resolution corresponding to the second profile tested, 480p. A low, good quality bitrate value was detected individually for each of the sixteen sequences using the BitDetect mechanism. For the sequences corresponding to the 360p profile, the bitrate was detected as 512 Kbps for the Sleep A sequence and 256 Kbps for the other seven sequences. For the sequences corresponding to the 480p profile, the bitrate was detected as 768 Kbps for the Sleep B sequence and 384 Kbps for the other seven sequences. This suggests that documentaries usually require higher bitrate due to the higher content dynamicity. The encoding characteristics of the sixteen test sequences are presented in Table 3. The original frame-rate of the clips was maintained, while the rest of encoding settings (e.g. audio bitrate) were maintained constant across the sequences.

Test Sequence	Length [sec]	Video Codec	Reference Resolution [pixels]	Video Bitrate [kbps]	Frame Rate [fps]	Audio Encoding Settings
Arts A / B	20 / 27	H.264	640x360 / 854x480	256 / 512	24	Audio Codec: AAC Audio Bitrate: 128 Kbps 2 channels (Stereo)
Dubus A / B	30 / 25			256 / 512	30	
Hotness A / B	30 / 30			256 / 512	24	
Hulu A / B	27 / 21			256 / 512	30	
Languagelab A / B	30 / 30			256 / 512	30	
Obesity A / B	30 / 30			256 / 512	30	
Sleep A / B	26 / 20			384 / 768	30	
Sol A / B	30 / 30			256 / 512	30	

Table 3: Encoding characteristics of the sixteen test sequences

Methodology

Each participant to the study was asked to view the sixteen test sequences encoded as presented in Table 3. The test sequences corresponding to the 360p profile were viewed first on a HP iPAQ 214 PDA with a 640x480 pixels resolution. The sequences corresponding to the 480p profile were viewed next on a Dell Inspiron Mini 10 netbook with a 1024x600 pixels resolution. Similar conditions were maintained for all the participants and standard recommendations (ITU-T 2009) for video quality assessment were followed.

After viewing each sequence, the participants were asked to rate their overall quality on a five-point scale (1-Bad, 2-Poor, 3-Fair, 4-Good, 5-Excellent) and to answer an educational question related strictly to the visual information presented in that clip. Twelve of the sixteen questions were multiple choice type with only one correct answer, two questions were yes/no type, and two questions were short answer type. An assumption was made that if learners are able to answer correctly the questions after viewing each clip only once, they are also able to acquire knowledge from the clip. The sound was maintained in order to replicate as much as possible a normal viewing experience. However, additional care was made that the answers to the questions are found solely in the video.

The decision to use different sequences from each clip for the two profiles was made in order to avoid influencing the answers provided by the participants. If the same sequence is displayed on both devices, a participant would have answered the first question after seeing only once the sequence on the first device, and the second question after viewing the sequence twice, on both devices. 21 (M = 13, F = 8) subject with ages between 21 and 37 years old (AVG = 27.14), have participated in the study.

Results

Video Quality Assessment Results

For each of the sixteen test sequences the video quality ratings on the 1-5 scale were averaged across all 21 participants, obtaining the Mean Opinion Scores (MOS). The standard deviation (STDEV) of the statistical distribution of the assessment ratings across the participants was also computed for each sequence.

The quality assessment results are presented in Figure 4. The results show that the majority of the sixteen sequences have scored close to 4 (Good). One sequence corresponding to the 360p profile (Languagelab A), and two sequences corresponding to the 480p profile (Arts B and Obesity B) have scored slightly lower than 4, but higher than 3.5. The average MOS scores for the two profiles are both equal with 4.1, while a t-test on the mean values indicate that there is no statistical difference in the final scores for the two profiles being tested ($\alpha = 0.01$, $t = 0.16$, t-critical = 2.99, $p(t) = 0.43$, $r = 0.81$). For both profiles the sequence with the lowest MOS score has the highest STDEV (Languagelab A, MOS = 3.6, STDEV = 1.12; Arts B, MOS = 3.7, STDEV = 1.10). The Pearson correlation further indicates that there is decreasing relationship between the MOS and STDEV values ($r = -0.678$ for 360p, $r = -0.732$ for 480p, $r = -0.704$ overall), thus the ratings across participants tend to have a higher variation, for the clips with lower perceived quality.

The quality results show that the bitrate values recommended by the BitDetect mechanism offer a good level of quality as perceived subjectively by learners, across different video profiles and different educational multimedia clips.

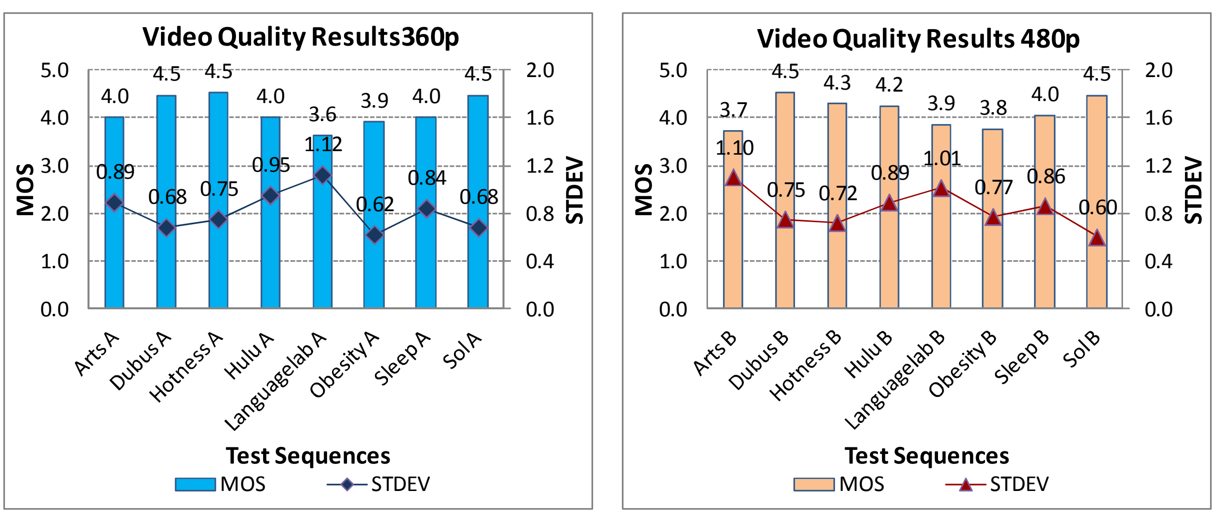


Figure 4: Subjective video quality assessment results for the two profiles

Knowledge Transfer Assessment Results

The second goal of the study was to assess if the quality is also good-enough for enabling learners to acquire knowledge from the clips. For each educational question corresponding to one of the sixteen test sequences, the total number of correct answers provided by the participants, and the average correct response rate was determined. The results presented in Figure 5, show that for the majority of the clips, the majority of the subjects have answered the questions correctly. Only for a single question, less than 50% of the participants have provided the correct answer, although the corresponding test sequence (Sleep B) has achieved a MOS equal to 4. Statistical analysis on this data set also shows that there is no relationship between the MOS scores and the number of correct answers ($r = -0.357$ for 360p, $r = 0.165$for 480p, $r = 0.015$ overall). Although the average correct response rates of 91% (360p) and 85% (480p), indicate that the bitrate values provide a good-enough quality for enabling knowledge transfer, further testing is needed for detecting how the video quality impacts the learning outcome.

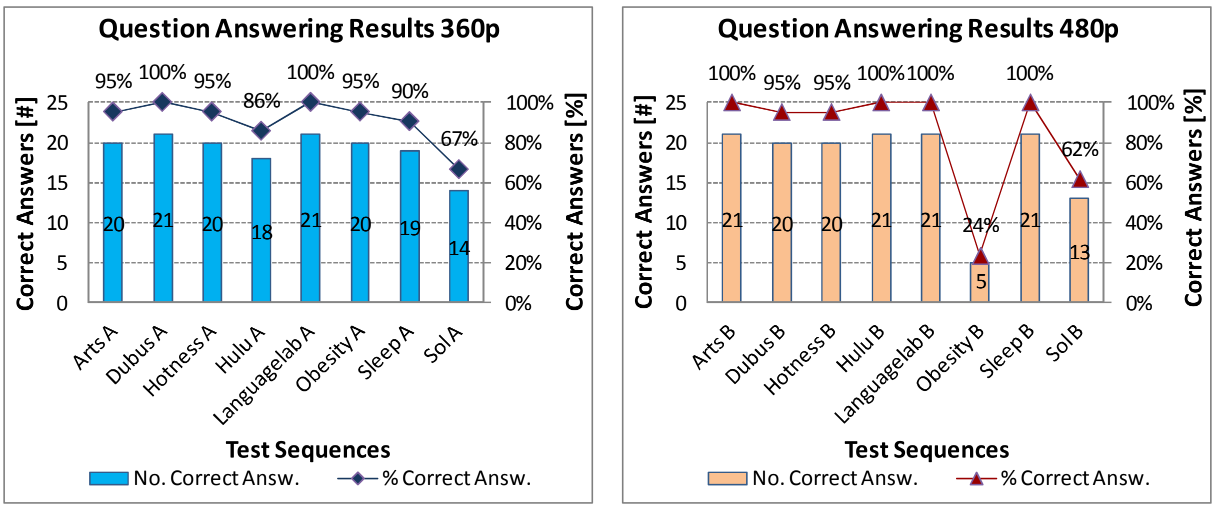


Figure 5: Numbers and percentages of correct answers to the educational questions for the two profiles

Conclusions

This paper presented a solution for enabling educational multimedia content personalization and adaptation in m-learning systems. Device screen resolution driven personalisation and available wireless network bandwidth driven adaptation are targeted. To enable personalisation based on learner device screen resolution mobile devices were grouped in four classes depending on their screen resolution: Large Screen Resolution Devices, Medium-Large Screen Resolution Devices, Medium-Small Screen Resolution Devices and Small Screen Resolution Devices. Video profiles consisting of recommended encoding settings are proposed for each device class. To enable educational multimedia content adaptation based on the available bandwidth, low video bitrate values still offering good quality levels are detected using the BitDetect mechanism.

A subjective study was conducted to assess if the bitrate values recommended by BitDetect for the eight educational multimedia clips encoded at two different resolutions are suitable for m-learning. The results have shown that the bitrate values offer a good quality for the majority of the test sequences, a 4.1 score (Good on a 1-5 scale) being achieved on average. Furthermore, the results have confirmed that the bitrate thresholds offer a good-enough quality for enabling knowledge transfer, as overall the subjects have answered correctly to questions related to the information presented in the clips in 88% of the cases.

Acknowledgements

The support of IRCSET (Irish Research Council for Science, Engineering & Technology) Embark Initiative is greatly acknowledged.

References

ABI Research. (2011). Apple iPad Held 85% Media Tablet Market Share in 2010. Retrieved from http://www.abiresearch.com/press/3665-Apple+iPad+Held+85%25+Media+Tablet+Market+Share+in+2010

Ally, M., Lin, F., McGreal, R., & Woo, B. (2005). An Intelligent Agent for Adapting and Delivering Electronic Course Materials to Mobile Learners. Presented at the *4th World Conference on Mobile Learning (mLearn 2005)*, Cape Town, South Africa. Retrieved from http://www.mlearn.org.za/CD/papers/Ally.pdf

Brusilovsky, P., & Millán, E. (2007). User Models for Adaptive Hypermedia and Adaptive Educational Systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.), *The Adaptive Web*, Lecture Notes in Computer Science (Vol. 4321, pp. 3-53). Berlin, Heidelberg: Springer-Verlag.

Chang, Y.-C., Kao, W.-Y., Chu, C.-P., & Chiu, C.-H. (2009). A Learning Style Classification Mechanism for E-Learning. *Computers & Education*, *53*(2), 273-285.

De Bra, P., Aerts, A., Berden, B., de Lange, B., Rousseau, B., Santic, T., Smits, D., et al. (2003). AHA! The Adaptive Hypermedia Architecture. *Proceedings of the 14th ACM Conference on Hypertext and Hypermedia.* Nottingham, UK. 81-84.

Graf, S., Yang, G., Liu, T. C., & Kinshuk, D. (2009). Automatic, Global and Dynamic Student Modeling in a Ubiquitous Learning Environment. *Knowledge Management & E-Learning: An International Journal (KM&EL)*, *1*(1), 18-35.

In-Stat. (2011). More Than Half of US Handset Shipments Will be Smartphones by 2012, Worldwide Smartphone Shipments Move Toward 1 Billion by 2015. Retrieved from http://www.instat.com/newmk.asp?ID=3012&SourceID=00000501000000000000

ITU-T. (2008). *P.910: Subjective video quality assessment methods for multimedia applications*. Geneva, Switzerland: International Telecommunication Union. Retrieved from http://www.itu.int/rec/T-REC-P.910-200804-I/en

Kaufman, P., & Mohan, J. (2009). Video Use and Higher Education: Options for the Future. New York, USA: Intelligent Television, New York University. Retrieved from http://library.nyu.edu/about/Video_Use_in_Higher_Education.pdf

Kim, S., & Yoon, Y.-I. (2009). Adaptation E-learning Contents in Mobile Environment. *Proceedings of the 2nd International Conference on Interaction Sciences: Information Technology, Culture and Human* (*ICIS '09)* (pp. 474–479). New York, NY, USA: ACM

Liaw, S.-S., Hatala, M., & Huang, H.-M. (2010). Investigating Acceptance toward Mobile Learning to Assist Individual Knowledge Management: Based on Activity Theory Approach. *Computers & Education*, 54(2), 446-454.

Meeker, M. (2009). Economy + Internet Trends. Presented at the 2009 Web 2.0 Summit, San Francisco, CA. Retrieved from http://www.morganstanley.com/institutional/techresearch/pdfs/MS_Economy_Internet_Trends_102009_FINAL.pdf

Moldovan, A.-N., & Muntean, C. H. (2009). Personalisation of the Multimedia Content Delivered to Mobile Device Users. Presented at *4th IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB '09)*, Bilbao, Spain. doi:10.1109/ISBMSB.2009.5133750

Moldovan, A.-N., Molnar, A., & Muntean, C. H. (2011). EcoLearn: Battery Power Friendly e-Learning Environment for Mobile Device Users. In A. Lazakidou & I. El Emary (Eds.), *Learning-Oriented Technologies, Devices and Networks - Innovative Case Studies* (pp. 273-296). Saarbrücken, Germany: LAP LAMBERT Academic Publishing.

Moldovan, A.-N., Moraru, C. A., & Muntean, C. H. (2011). MediaMTool: Multimedia Content Management Tool. Presented at *6th IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB '11)*, Metropolitan Area Nuremberg, Germany. doi:10.1109/BMSB.2011.5954907

Muntean, C. H. (2008). Improving learner quality of experience by content adaptation based on network conditions. *Computers in Human Behavior*, *24*(4), 1452-1472.

Muntean, C. H., & Muntean, G.-M. (2009). Open corpus architecture for personalised ubiquitous e-learning. *Personal and Ubiquitous Computing*, *13*(3), 197-205.

Muntean, V. H., & Muntean, G.-M. (2009). A Novel Adaptive Multimedia Delivery Algorithm for Increasing User Quality of Experience during Wireless and Mobile E-learning. Presented at *4th IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB '09)*, Bilbao, Spain. doi:10.1109/ISBMSB.2009.5133739

Quinn, C. (2008). mLearning Devices. Quinnovation. Retrieved from http://quinnovation.com:8000/MobileDevices.pdf

Schwarz, H., Marpe, D., & Wiegand, T. (2007). Overview of the Scalable Video Coding Extension of the H.264/AVC Standard. *IEEE Transactions on Circuits and Systems for Video Technology*, *17*(9), 1103–1120.

Wang, Z., & Bovik, A.C. (2009). Mean squared error: Love it or leave it? A new look at Signal Fidelity Measures. *IEEE Signal Processing Magazine*, *26*(1), 98-117.

Wang, Z., Lu, L., & Bovik, Alan C. (2004). Video Quality Assessment Based on Structural Distortion Measurement. *Signal Processing: Image Communication, Special Issue on "Objective Video Quality Metrics"*, *19*(2), 121–132.

Wiegand, T., Sullivan, G. J., Bjontegaard, G., & Luthra, A. (2003). Overview of the H. 264/AVC video coding standard. *IEEE Transactions on Circuits and Systems for Video Technology*, *13*(7), 560–576.

Yin, C., Ogata, H., Tabata, Y., & Yano, Y. (2010). Supporting the Acquisition of Japanese Polite Expressions in Context-Aware Ubiquitous Learning. *International Journal of Mobile Learning and Organisation (IJMLO)*, *4*(2), 214–234.

Zambelli, A. (2009). IIS Smooth Streaming Technical Overview. Microsoft Corporation. Retrieved from http://dvb-crew.atw.hu/applications/documents/IIS_Smooth_Streaming_Technical_Overview.pdf

Zhao, X., & Okamoto, T. (2008). A Device-Independent System Architecture for Adaptive Mobile Learning. *Proceedings of the 8th IEEE International Conference on Advanced Learning Technologies 2008 (ICALT '08),* Santander, Spain. 23-25.