UNIVERSIDADE DA BEIRA INTERIOR
Engenharia

Entropy-Based Dynamic Ad Placement Algorithms for In-Video Advertising

Tiago Alexandre Fonseca Ribeiro Ferreira

Dissertação para obtenção do Grau de Mestre em
Engenharia Informática
(2° ciclo de estudos)

Orientador: Prof. Doutor Abel João Padrão Gomes

Covilhã, Junho de 2014

Dedicado à minha família e todos os que me ajudaram nesta jornada.

Dedicated to my family and all who have help me in this journey.

Agradecimentos

Com esta dissertação de mestrado, chega assim o fim de mais um ciclo na minha vida, um ciclo cheio de trabalho, dedicação, mas também de muito divertimento e satisfação por tudo o que consegui alcançar.

Contudo, nada disto seria possível sem a ajuda de todos aqueles que me acompanharam ao longo deste ano e aos quais dedico esta dissertação.

Ao meu orientador Professor Doutor Abel Gomes, pela sua ajuda e orientação incessável, que ao longo destes últimos anos me aconselhou em qual era o caminho a seguir, pela porta sempre aberta e disponível para tirar toda e qualquer dúvida.

À empresa *EyeSee* em especial ao João Redol, pelo suporte financeiro e pelas oportunidades que me foram concedidas e por acreditarem que poderia desenvolver um bom trabalho e a quem espero e acredito não ter desiludido.

Ao Professor Doutor Nuno Garcia, que tornou este projecto possível e pela oportunidade e apoio que me concedeu.

À minha família e em especial à minha mãe, pelos muitos esforços e sacrifícios que fizeram ao longo de todos estes anos da minha vida, que me apoiaram e ensinaram a lutar e a nunca desistir dos meus objectivos.

Aos meus amigos, particular, ao Gonçalo Amador, à Sabrina Guia, ao Sérgio Dias e ao Pedro Tavares que propocionaram momentos de descontração e lazer, sem os quais seria muito mais difícil conseguir concluir esta dissertação.

Por último a todos aqueles que direta ou indiretamente me ajudaram em todo esta jornada.

Acknowledgements

With this thesis, it comes the end of another cycle in my life, a cycle full of work, dedication, but also a lot of fun and satisfaction for what I have achieved.

However, none of this would be possible without the help of all those who have accompanied me throughout this year and to whom I dedicate this dissertation.

To my advisor Professor Abel Gomes, PhD, for his help and unceasing guidance, who over these last years has advised me in the right way, who always had an open door to help me in any of my doubts.

To *EyeSee* in particular to João Redol, for the funding support and opportunity that are given to me, and for the belief that I could do good job.

To Professor Nuno Garcia, PhD, who made this project possible and for the opportunity and support that he gave me.

To my family, particularly to my mother, for the many efforts and sacrifices they have made over all these years of my life, who have supported me and taught me to fight and never give up on achieving my goals.

To my friends, in particular to Gonçalo Amador, Sabrina Guia, Sérgio Dias and Pedro Tavares, for the relaxing and leisure moments, without whom it would be much more overwhelming to complete this dissertation.

Finally to all those who directly or indirectly have helped me throughout this journey.

Resumo

Com a evolução da Internet e o número crescente de utilizadores ao longo destes últimos anos, a publicidade on-line tornou-se um dos modelos base que tem sustentado muitos negócios na Internet. Da mesma forma, vídeos on-line constituem uma parte significativa do tráfego na Internet. É por isso possível entender desta forma, o potencial que ferramentas que possão explorar eficientemente ambas estas áreas possuem no mercado.

Nesta dissertação será feita uma revisão da história da publicidade online, mas também será apresentado ao leitor uma revisão sobre o estado da arte das principais contribuições científicas para a publicidade on-line, em especial para a publicidade em video.

Na publicidade em vídeo, uma das principais preocupações é identificar os melhores locais para a inserir os anúncios. Na literatura, este problema é abordado de diferentes maneiras, alguns criaram métodos para gêneros específicos de vídeo, por exemplo, futebol ou ténis, outros métodos são independentes do gênero, mas tentam identificar as cenas de vídeo (um conjunto contínuo de frames relacionadas) e apenas exibir anúncios neles.

No entanto, a grande maioria dos vídeos on-line na Internet não são suficiente longos para serem identificadas cenas suficientemente longas para inserir os anúncios. Assim, nesta dissertação iremos abordar uma nova solução para a inserção de anúnicios em vídeos, uma solução que pode ser utilizada de forma independente da duração e gênero do vídeo em questão.

Ao desenvolver uma solução para inserir anúncos em vídeos a grande preocupação recai sobre a intromissão que o anúncio inserido poderá ter sobre o utilizador. A intrusão está relacionada com o local e tempo utilizado pela publicidade quando é inserida. Por estas razões, o algoritmo tem que levar em consideração "onde", "quando" e "como" o anúncio deve ser inserido no vídeo, de modo que seja possível reduzir a intromissão dos anúncios para o utilizador.

Em suma, para além de ser independente da duração e gênero do vídeo, o método proposto será também desenvolvido tendo em consideração a intromissão do anúncio para o utilizador. Por fim, o método proposto será testado e comparado com outros métodos, de modo a que seja possivel perceber as suas capacidades.

Palavras-chave

Análise de vídeo, processamento de vídeo, publicidade on-line, publicidade em vídeo.

Abstract

With the evolution of the Internet and the increasing number of users over last years, online advertising has become one of the pillars models that sustains many of the Internet businesses.

In this dissertation, we review the history of online advertising, will be made, as well as the state-of-the-art of the major scientific contributions in online advertising,in particularly in respect to in-video advertising.

In in-video advertising, one of the major issues is to identify the best places for insertion of ads. In the literature, this problem is addressed in different ways. Some methods are designed for a specific genres of video, e.g., football or tennis, while others are independent of genre, trying to identify the meaningful video scenes (a set of continuous and related frames) where ads will be displayed.

However, the vast majority of online videos in the Internet are not long enough to identify large scenes. So, in this dissertation we will address a new solution for advertisement insertion in online videos, a solution that can be utilized independently of the duration and genre of the video in question.

When developing a solution for in-video advertising, a major challenge rests on the intrusiveness that the ad inserted will take upon the viewer. The intrusiveness is related to the place and timing used by the advertising to be inserted. For these reasons, the algorithm has to take in consideration the "where", "when" and "how" the advertisement should be inserted in the video, so that it is possible to reduce the intrusiveness of the ads to the viewer.

In short, in addition to besides being independent of duration and genre, the proposed method for ad placement in video was developed taking in consideration the ad intrusiveness to the user.

Keywords

Video analysis, video processing, online advertisement, in-video advertisement.

Contents

List of Figures

List of Tables

List of Algorithms

List of Abbreviations

Ad	Advertisement
CPM	Cost Per Mile
DHTML	Dynamic HyperText Markup Language
FPS	Frames Per Second
HSV	Hue, Saturarion, Value
HTML	HyperText Markup Language
IAB	Internet Advertising Bureau
MPEG	Movie Picture Experts Group
PEP	Personal Expression Platform
PGM	Portable Gray Map
PPC	Pay-per-click
RGB	Red, Green, Blue
ROI	Region Of Interest
UBI	University of Beira Interior
WebCam	Video capture device
WWW	World Wide Web

Chapter 1

Introduction

Advertising can be defined as the act of drawing the attention of consumers to a product, service or idea in a public medium, in order to promote it. The way this promotion has been made by advertisers has changed through history and has been in direct relation with the available media to society.

1.1 Motivation

It is dificult to say when humans created the concept of advertising. It is believed that advertising began more or less when people started to trade products among them [Pre00]. There are even records reporting the use of advertising in ancient times [SF87] [Gop10] [Cha95].

With the rise of information society, advertisement has reinvented itself to adapt to the needs of society but also to the available media, such as the TV, radio or billboards. The fact is that, when a new medium became available, advertising in the other media starts to loose their effectiveness.

One of these available media is the Internet. In this dissertation we are interested in as online advertising or Internet advertising, that is advertising across the Internet. Ha [Ha08] has defined online advertising as being "deliberate messages placed on third-party websites including search engines and directories available through Internet access". Online advertisement began from companies, such as, CompuServe, AOL, and Prodigy, where their online services included ads of products from other companies products. The emergence of the *World Wide Web* as we know it today, as led us to find out new methodologies for advertising done online, what has made online advertising one of biggest online investment areas [Sil13b].

A recent study conducted by the Internet Advertising Bureau (IAB) and PriceWaterhouseCoopers (PWC) [Sil13b], has shown that, in the first half of 2013, the online advertising revenues reached $20.1 billion dollars, a growth of 245% if compared to the revenues of the year of 1996.

Advertising can be displayed in many different ways over the Internet; for example, utilizing search engines or web pages. Other form of displaying online advertising is in videos, more specifically doing what is known as *in-video advertising* (advertising insertion in videos). Online videos have had an exponential growth. In a study, delivered by *Cisco* in 2013, regarding the Internet traffic of 2012 [Cis13], it was estimated that 57% of Internet traffic was online video (P2P not included), and that by 2017 this mark will be of 69%. These statistics emphasize the dimension that online videos has over the Internet nowadays.

Also *Youtube*, one of the major websites that allows the hosting and sharing of videos online, has about 1 billion of unique users every month, who watch 6 billion hours of video each month, having 100 hours of video been uploaded to *Youtube* every minute in the year of 2013 [Goo13]. Aside *Youtube*, one must consider hundreds of other sharing video websites such as, for example, *Dailymotion, Netflix, Muzu, Flickr* and so on, which gives a perspective about the importance of having efficient methods for in-video online advertising .

In-video advertising is a complex field of study because it involves different topics in computer science, including intelligent systems, computer vision, video processing and analysis, and computer graphics.

1.2 Problem statement and Goals

Ads (i.e. advertisements) hve to be inserted without interfering with the natural movement of the objects present in the scene of the video. The objective is to insert advertising during the displaying of the video, not before or after the beginning or ending of the video like the pre-roll and post-roll advertising.

In-video advertisement is a very complex task to achieve. There are two aspects that are needed to always bear in mind the placement in order to have a successful algorithm of this kind, the placement and the timing of the advertising. The first is that the advertisement cannot occlude any relevant objects in the scene, in order to not disturb the visualization of the video. Second, the inserted advertisement has to be on screen enough time so that the viewer realize its message.

Advertisement should be inserted in the background of the video, that is regions where there isn't any relevant scene object. However, it is hard to find this background when it changes from frame to frame. For example, the features that can be extracted from a football game (green court, midfield line, goal posts) are completely different from the ones found in a movie trailer, where scenes with special affects change at high pace at any moments, that is there are are no specific placements known *a priori* to place ads.

In short, the main goal of this dissertation is to find a possible solution that is capable of inserting online advertisements in a non-intrusive way for the most online videos without any prior knowledge about them.

1.3 Scheduling the Research Work

The research work that has led to the present dissertation involved a number of steps namely:

- Study and understanding of the problem of inserting advertisement in online videos.
- Review the literature on algorithms related to content insertion on online videos and to online advertisement in general.
- Study and development of solutions for the problem of inserting advertisement on online

videos.

- Testing and assessment of solutions performance.
- The writing of this dissertation.

This work was funded by *EyeSee* Ltd. The development of the project took place at MediaLab and ALLab, Department of Computer Science, UBI.

1.4 Dissertation Organization

In general terms, this dissertation consists of four chapters, and is organized as follows:

- **Chapter 1** is the current chapter. It briefly introduces the topic of online advertising. This chapter also addresses the motivation behind this dissertation and the goals to be accomplished by this work.
- **Chapter 2** overviews the current state-of-the art in online advertising. In the first section a brief history of online advertising is presented, this is followed by a classification of the different types of online advertising, were an insight of the technologies and the main methods for each advertising type is provided.
- **Chapter 3** provides a detailed description of an entropy-based algorithm for ad placement in videos. This chapter also presents the results of the proposed algorithms. Furthermore, those results are discussed and compared with the ones of other method in order to better evaluate the performance of the proposed algorithm.
- **Chapter 4** concludes this dissertation and presents some points for improvement in the future.

1.5 Contributions

The main contributions of the present work is an ad placement algorithm for short videos that outperforms the state-of-the-art algorithms. Besides, this work has originated the writing of the following two papers:

1. Tiago Ferreira, Dominik Wegrzyn, Nuno Garcia, João Redol and Abel Gomes. "Online Advertising: A Review" (Submitted to ACM Transactions on the Web).
2. Tiago Ferreira, Nuno Garcia, João Redol and Abel Gomes. "Entropy-Based Dynamic Ad Placement Algorithm for In-Video Advertising" (Submitted to IEEE Transactions on Multimedia).

1.6 Target Audience

The scope of this dissertation lies in computer vision, graphics and multimedia. This dissertation can be considered relevant to all programmers and researchers in these knowledge fields and to all who are interested in online advertisement, in particular to in-video advertising.

Chapter 2

Online Advertising: the State-of-the-Art

In this chapter it will be made a review on the history and the state-of-the-art of online advertisement. In the first section (section 2.1) starting in the early 70s until the current times a brief review of the history of online advertising will be taken, it will be presented the foundation of online advertisement and the major companies that have invested in this area. The following Section 2.2 the technologies and display methods behind the different online advertising types will be explained. On section 2.3 will be present the different types of online advertising and what separate them from the others, being the last section utilized to explain the major contributions of each advertising category.

2.1 A Brief History of Online Advertising

In this section we briefly review the history of online advertising. Before the Internet as we know it to be today, online services such CompuServe, AOL and Prodigy promoted a variety of products alongside with their services and thus dominated the online advertising market, from the 80s to the middle 90s. However, the invention of World Wide Web and the first graphics browser in the early 90s revolutionized our lives, in particular the online advertising as we know it today.

2.1.1 CompuServe

CompuServe was founded in Columbus, Ohio in 1969, having become the first online commercial service in the United States of America. Among the provided services, we highlight the email system for personal computers in 1979, provision of wide-area networking capabilities in a national and international scene in 1982, and, finally, the invention of the GIF image format [Nic94] that allowed basic animation.

The technique used by CompuServe for advertising products consisted mainly of text pages, but later on with Internet evolution they started to use images, as shown in Figure 2.1. CompuServe dominated the field during the 80s up to mid-90s, until they merged with the American Online (AOL).

2.1.2 America Online

William Von Meister created the CVC (Control Video Corporation) and the GameLine service for the Atari 2600 video game console in the beginning of the 80s. With this service, its subscribers could download games using a telephone line according to an hourly fee. Although it was an

Figure 2.1: CompuServe start up page [Wag93].

innovative idea, the project was a failure and five years later Von Meister ended up to abandon it.

Jim Kimsey become the CEO of the reborn company then named Quantum Computer Services, that was renamed to America Online in the early 90s [Swi98]. AOL released various services at that time such as Q-Link, a bulletin board service for Commodore 64. In 1989, AOL also launched an instant messenger service, welcoming its users with the famous *''You've got mail!"*, with the goal of complementing their online gaming services.

With its growing success, AOL started to compete with CompuServe for the place of major online service, and eventually surpass it by means of changing their marketing campaign. Until 1996 both services, AOL and CompuServe, were provided in return for hourly fees. 1996, AOL (Figure 2.2) changed this procedure, and started to charge monthly fees, what allowed them an exponential growth in revenues. AOL acquired CompuServe in 1998.

2.1.3 Prodigy

The main idea behind Prodigy (1980) was originally taken from CBS and AT&T. They dreamed of a device that allowed consumers to shop from their own homes. It was only in February of 1984, that CBS, IBM and Sears created such a device. Just like others before them, Compuserve and AOL, a hourly fee was also charged by using their services. However in order to be competitive with other online services, Prodigy decided to use a different approach in advertising, more

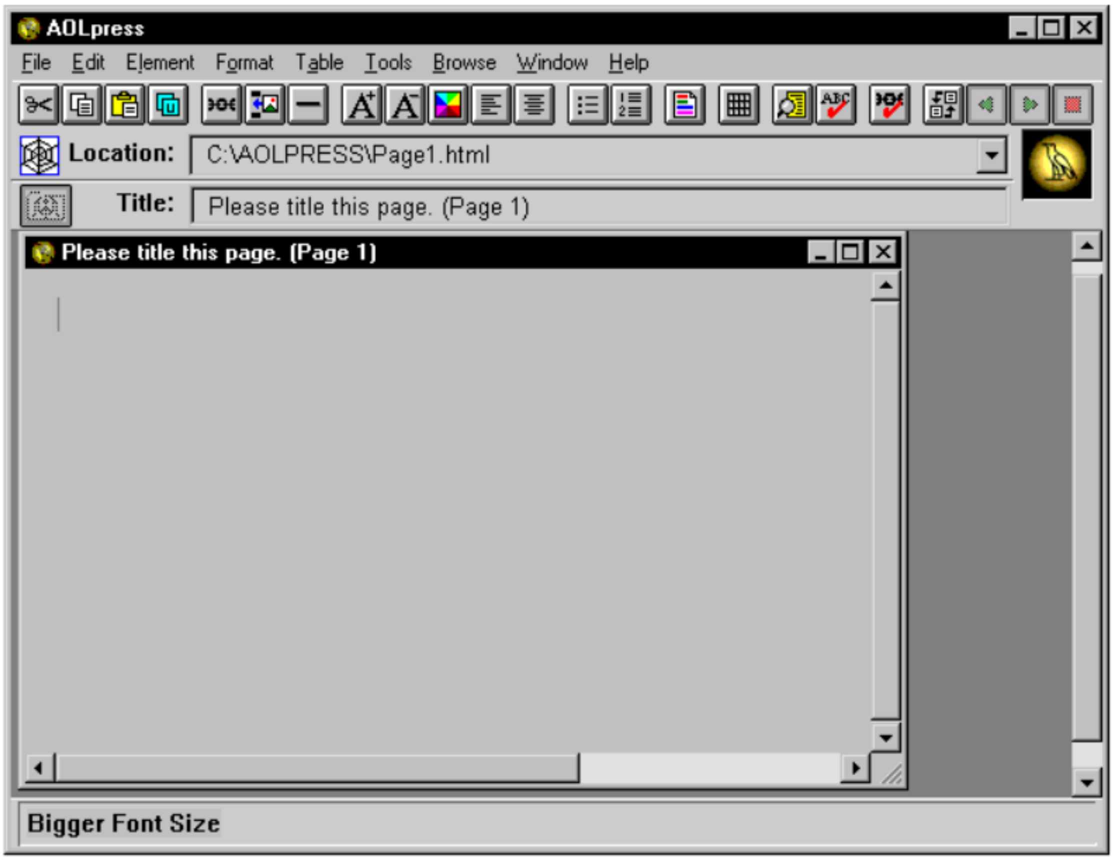


Figure 2.2: AOL start up page [DeG97].

specifically Prodigy claimed they were providing the only service that put ads on almost every screen handled by the user in his/her daily life. Advertisers were paying between $\$10,000$ and $\$20,000$ to Prodigy to design these ads on their user interfaces [Her94], what made Prodigy one of the first dial-up services that offered both web access and web hosting to its members (Figure 2.3).

2.1.4 Minitel

Although France Telecom had developed the Minitel in 1970, it only started being distributed in France after 1982. The main idea behind this project was to reduce costs for France Telecom replacing non-business telephone directories by their digital equivalent. Let us say that France Telecom had already developed other online services before advertising services for Minitel, such as the dating site known as *Minitel Rose* (Figure 2.4), news, gaming, shopping, well as the pioneering services of electronic banking [CBJ94]. Although it has not been able to impose itself to the rest of the world, Minitel did spread itself across Europe and became the biggest and most successful online service in the continent. With the advent of the world wide web (WWW), Minitel lost the competition to WWW [BL04] [ST12], but even so it remained operational until June 2012.

Figure 2.3: Prodigy: online journal [Vie91].

2.1.5 World Wide Web

In 1989, Tim Berners-Lee at CERN (Conseil Europeen pour la Recherche Nucleaire, Geneva, Switzerland) had the idea of linking and accessing information of various sorts over a web of nodes across which the user would be able to browse at will, what later originated the WWW (World Wide Web) [BL00]. The WWW was initially devised to allow sharing information between scientists and institutes over the world. In April 1993, CERN released the web as an open licence, in order to maximise its dissemination. The development of the WWW technology is currently made by the World-Wide Web Consortium (`htpp://www.w3.org`).

2.1.6 NCSA Mosaic

Created by NCSA (National Center for Supercomputing Applications, `http://www.ncsa.illinois.edu`) in 1992, Mosaic was the first graphics browser for the Unix X Window System (Figure 2.5) and is considered by many as one of the main reasons for the success of WWW. Because of its potential, from a commercial point of view, Mosaic is seen as the milestone that marked the beginning of decline of online services like Prodigy, CompuServe and AOL, which then would loose the market shares in online advertising [Wol94].

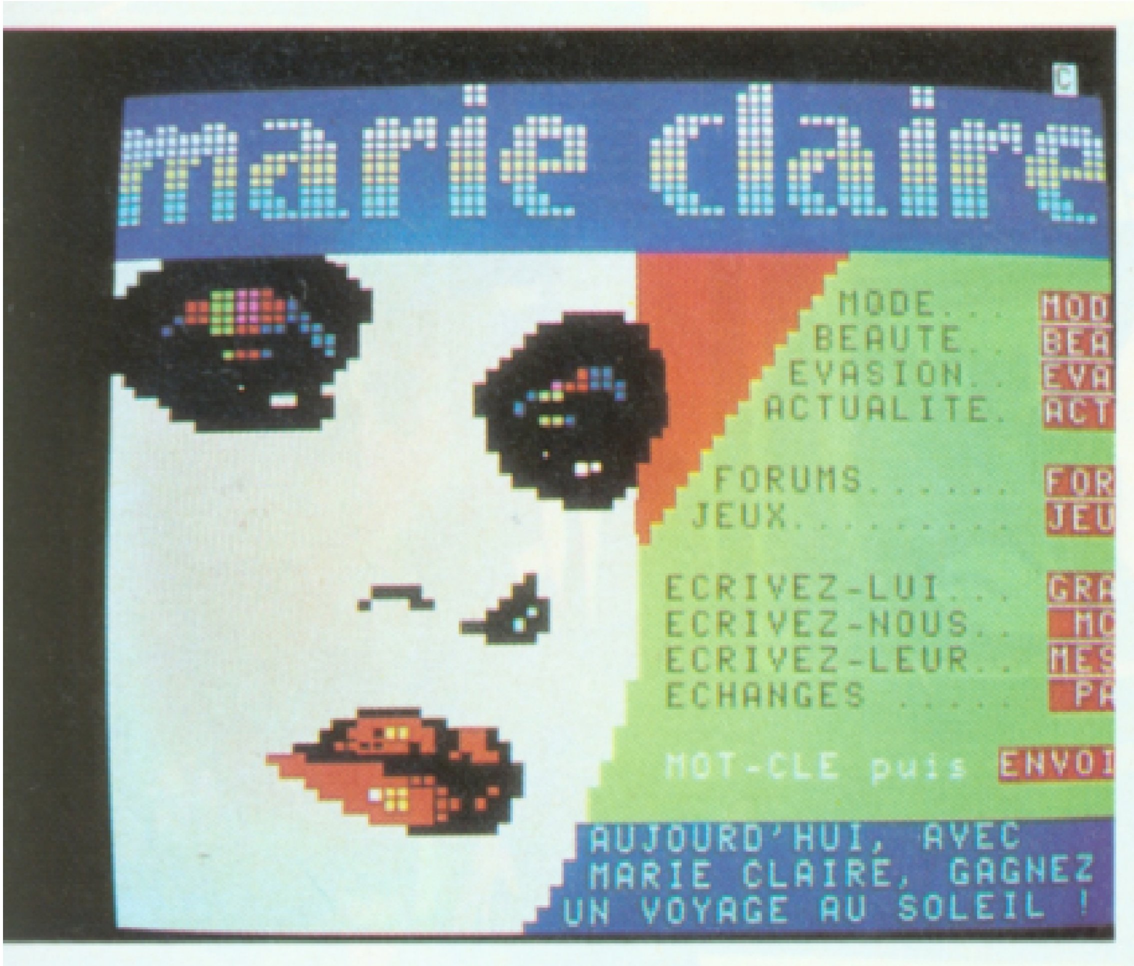


Figure 2.4: Minitel Rose: user dating page [Web13].

2.1.7 NetScape: Cookies

In April 1994 Marc Andreessen and James Clark founded the Mosaic Communications, which was renamed almost immediately to Netscape Communications. Until that time, the data about the user actions, such as clicks and visited sites, were treated as an isolated event. There was not an automatic way to record any of this information in order to use it for other purposes, like advertising [Kri01]. Cookies were defined as a consumer tracking technology used to customize the contents of interest for users and make ads targeted to specific clients [Miy08].

In 1994, there came to be a need in keeping track the items chosen by the user, because until then the existent methods were not enough to solve this problem [KS05]. Lou Montulli had the idea of moving a small data packet (cookie) from the server to the user machine. This way the computer hosting the site could store a small text file with information about the user actions on the web page. Montulli's cookies became then a turning point not only for the web in general [Bay98], but also for web advertising because it was since then possible to outline the user profile.

According to Lawrence Lessig, it can be even said that the Web was a private place before the appearance of cookies, but, with cookies, the Web turned into a space with extraordinary monitoring capabilities [Sch01]. Because of the possibility of malicious actions through the use

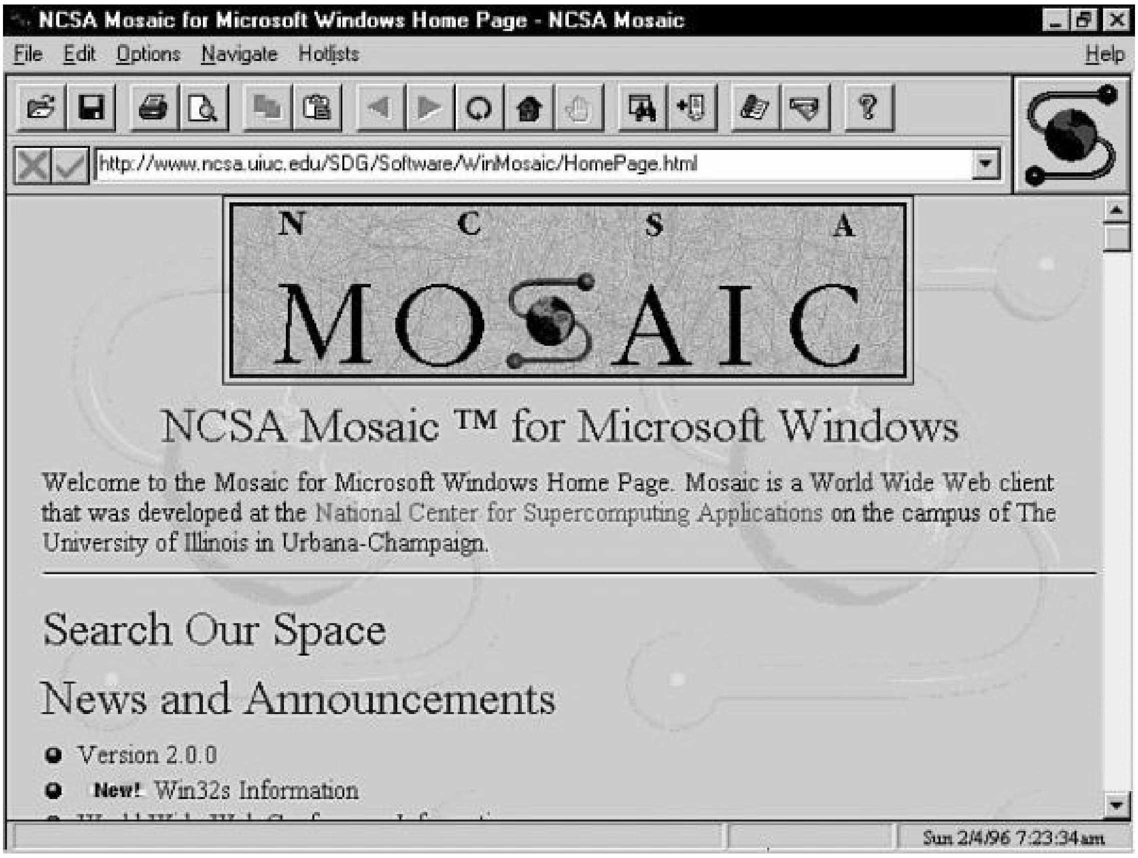


Figure 2.5: NCSA Mosaic graphic browser [Mos95].

of cookies, in May 2011, the European Union released a directive known as the cookie law. The cookie law is a regulation requiring the websites to obtain consent from users to store or retrieve any information of any device that is connected to the web [Mof12].

2.1.8 Hot Wired: Banner

In 1993, E-Media was founded by Ken McCarthy, an expert at the possibilities of the new media and a marketing advisor for the BBS community. One year later he proposed a new notion of a clickable/trackable ad, called *banner*, during the First Internet Marketing Conference held in San Francisco [MGA94]. Interestingly, the value at which banners were sold was measured according to the number of times that the ad was clicked.

Few years later, the "like" system used by Overture and Google proved its effectiveness as a clickable model. Rick Boyce was about receiving a proposal to be the business development director of HotWired, so that Wired Magazine was then launched in the Autumn of 1994. He was responsible for selling the first banners and had successfully increased the revenues of the company.

HotWired created the first banner, which had a resolution of 468×60 pixels and had the following inscription: "Have you ever clicked your mouse right here? You will." and also introduced the term "banner ad", Figure 2.6. This first ad obtained 42% click rate and was a defining moment in the Web history.

Figure 2.6: The first banner [Rei97].

2.1.9 O'Reily's Global Network Navigator

Although HotWired had revolutionized the Web advertisement with ad banners, Dale Dougherty (co-founder of O'Reilly Media) likely was who developed the first commercially supported web pages. O'Reilly's Global Network Navigator (GNN) was using paid advertising based on image and had one banner ad on the homepage. HotWired got the fame for the creation of the first clickable ads, but, according to O'Conell, founder and chairman of Modern Media (`http://modernmedia.com/`), GNN created those clickable ads two or three weeks earlier. Besides, some also believe that the first ad banners were used sooner than O'Conell stated, because apparently GNN had already clickable ads in 1993.

2.1.10 DoubleClick

In late 1995, Kevin O'Connor and Dwight Merriman came up with the Internet Advertising Network (IAN). They moved from Georgia to New York to be closer to media companies and advertising agencies and renamed it to DoubleClick. Wenda Millard joined the company as executive vice president. Her move brought credibility to the company and made possible to DoubleClick display ads across thousands of sites [Kel96]. In 1998, DoubleClick managed to have the third largest audience on the Internet (behind AOL and Yahoo) [HIH14].

The online advertising network of the company was based on cookies. Cookies were used to recognize the users when they visited their network. DoubleClick made also possible an ad rotation, what resulted in a bigger diversity of ads for each user. At that time, no other medium was able to make such a customized advertising [KS05].

Privacy advocates suggested that third-party cookies could be a problem, as they make possible to build a detailed profile about the users habits. In 1999, DoubleClick acquired the Abacus Direct for 1.7 billion dollars, becoming a matter of concern for the Federal Trade Commission [HIH14]. In 2004, Doubleclick also acquired Performics, a company specialized in search engine optimization and search engine marketing solutions. Because of these acquisitions Doubleclick aroused the interest of Google, which then bought Doubleclick in April 2007 [Vai11].

2.1.11 Internet Advertising Bureau

The displaying of advertising kept on growing and many web sites decided to grant space for advertising. The assumption was that more ads means more revenue, which resulted in pages full of advertising of all types, shapes and sizes.

In 1998, Meadows-Klue (brand manager of the Telegraph.co.uk, the first online newspaper created in 1995 [Kav98]) co-founded the Internet Advertising Bureau (IAB). His idea was to

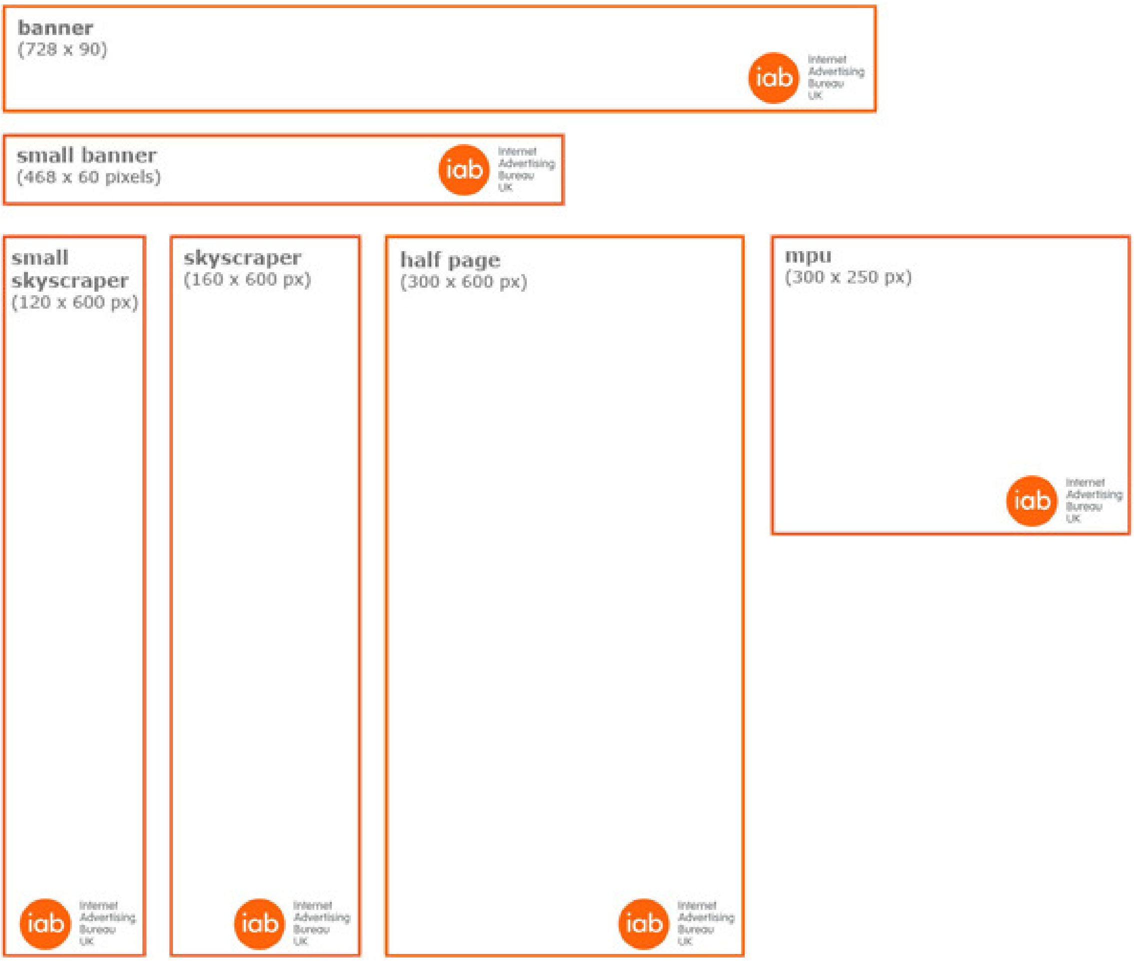


Figure 2.7: IAB universal ad package, the six formats [Cam13].

protect the freedom of advertising, rather than support new ad formats. In his opinion, this would lead to a better share of information and, expectedly, also to the development of other technologies, other than the banner format [RB98].

In 2001, given the advertising boom on Internet, the IAB analyzed 250 advertising formats that were being used at the time, having then defined seven standard formats as a way of stopping the uncontrollable proliferation of new ad formats because, as it was then argued, the display and loading page response rates dropped significantly with so many formats to cope with whenever a new page was loaded and exhibited on the browser.

One year later these formats were revised and became the "Universal Ad Package", that contained only six ads formats, Figure 2.7. This package included four standard formats for banners and skyscrapers (i.e., vertical banners), so that media planners could focus on the ads themselves [MRT14] instead of worrying about the all the page.

2.1.12 Idealab

Pay-Per-Click (PPC) was created in 1994 by Idealab. The goal was to get paid for ads that were clicked by the user. This favors the click-based ad performance, rather than quantity of ads available to the public. PPC was a way to develop a commercial suited to indexing of the web search engines [MM07].

In 1997, the Idealab launched the search engine Goto.com and encouraged web sites to pay for a remarkable place in the web search results. This was the beginning of the PPC advertising model. The results were ranked according to the fee that sites would pay, since the search keywords were always available for bidding in an open auction [MM07].

In 1998, Goto.com became fully developed and started to use Inktomi's results. Recall that Inktomi was then considered as the best search engine before Google's [Ram12]. One year later, Idealab launched a real time tool that enabled advertisers to control their bidding [HJ12].

In 2001, the Idealab was renamed to Overture and started a partnership with Yahoo, in order to introduce paid ads in their search results. During the battle between MSN, Yahoo and Google for supremacy over the web, Yahoo bought the Overture for 2.2 billion dollars in late 2003 [FP06] .

2.1.13 Google

Larry Page and Sergey Brin met in 1995 at Stanford University. In 1996 they started developing a new search technology called BackRub, which was renamed to Google one year later. This system had the capability to analyze ''back links" that were pointing to web sites.

In 2000, Google.com was already available in ten languages and became officially the largest search engine over the web [VM05]. In the same year, Google launched the AdWords [RMJF09]. Using this technology, and after creating the ad, the advertiser was able to choose keywords that are related to his/her company. Every time that a user uses at least one of the keywords in a Google search, the ad can be presented side-by-side with the results (cf. Figure 2.11). This way it is possible to show up ads to people that likely may be interested in the kind of products that the company sells out. Those ads had four times more click through rates than the traditional banners. In 2002, Google made updates to AdWords, having included a new price that depended on the cost per click.

Later on (2003), Google acquired Applied Semantics for $102 million dollars, whose technology sustained the new AdSense service. The basic concept of AdSense lies in an advertising segmentation based on content. That is, AdSense is content-sensitive. In 2007, AdSense became also available on mobile searches.

In 2011, Google Adwords Express was launched, making the advertising directed even more toward user needs [MRT14]. Unlike AdWords, this new technology does not need any keywords. The ads of an enterprise are displayed only after people have searched on Google by products that the company sells, provided that such people are geographically near to the company. This service also signals on the Google Maps the place of the company. When the client clicks on one of these ads, he/she is redirected to the company web site or Google+ page [MRT14].

Thus, Google's strategy was to provide targeted advertisements, with the ads delivered together with the search results. This approach to advertising seemed to be profitable, especially as the rate of product sales increased [LZL12].

2.1.14 Big Data

Big Data is a new trend related to online advertising. A survey carried out by The Guardian in 2013 revealed that 86% of marketers believe that big data will change the marketing industry [QK96].

Big data is a mass of transactional and behavioral data that each of us creates in the daily use of the Internet, regardless of whether we use mobile devices or not, in particular when one purchases products or services, but also when we develop activities through social networks; more specifically, professional activities, entertaining activities, and socializing activities. In other words, big data aims at collecting the online footprint of each of us at the world scale.

Using the purchase history and location it is possible to understand and determine the needs of each age group from all the regions of the globe, what enables marketers to provide an online ad experience targeted to consumers. This has resulted in a greater objectivity in the product advertisement of each brand, and consequently in the increasing of revenues.

Nowadays, many types of online ads use data mining to extract user's data in order to better targeting ads towards users, as it is the case of mobile advertisement, search engine advertisement, and social networking advertisement [LZL12].

2.2 Ad Types and Technologies

An ad is normally built up using different media such as text, audio, image, video, or a combination of them. The design of an ad depends on the product that is supposed to be advertised, which in turn depends on the target audience to whom the product is intended for. There are several types of online ads, namely: *banners*, *pop-ups*, *email ads*, *snippet ads* and *rich media*. It is clear that the type of an ad depends on its underlying technology.

2.2.1 Email Ads

Email was first developed in 1972 by Ray Tomlinson at the BBN Technologies (`http://www.bbn.com`), and was initially thought of as a method of exchanging online messages between two entities. Email advertising usually consists in sending ads or soliciting sales using an email message (Figure 2.8). In the early, email ads were then limited to the textual form. Most of this advertising was done using a database or consumers or subscribers. But, soon many email ads became unsolicited messages for many users, so they started to be called spam.

The term *spam* was coined after the 25th episode of Monty Python Flying Circus comedy sketch, released on 15 December of 1970. Two costumers try to order their breakfast from a menu that had spam (the World War II canned meat) in every single dish. Later on, the association between these two terms were linked and the electronic term *spam* has become used to describe the email messages that contain advertising to a wide range of products and/or services and that the user could not get rid off. It is believed that the first spam message was delivered by DEC (Digital Equipment Corporation), announcing the new DEC-20 machine in 1978. The invitation

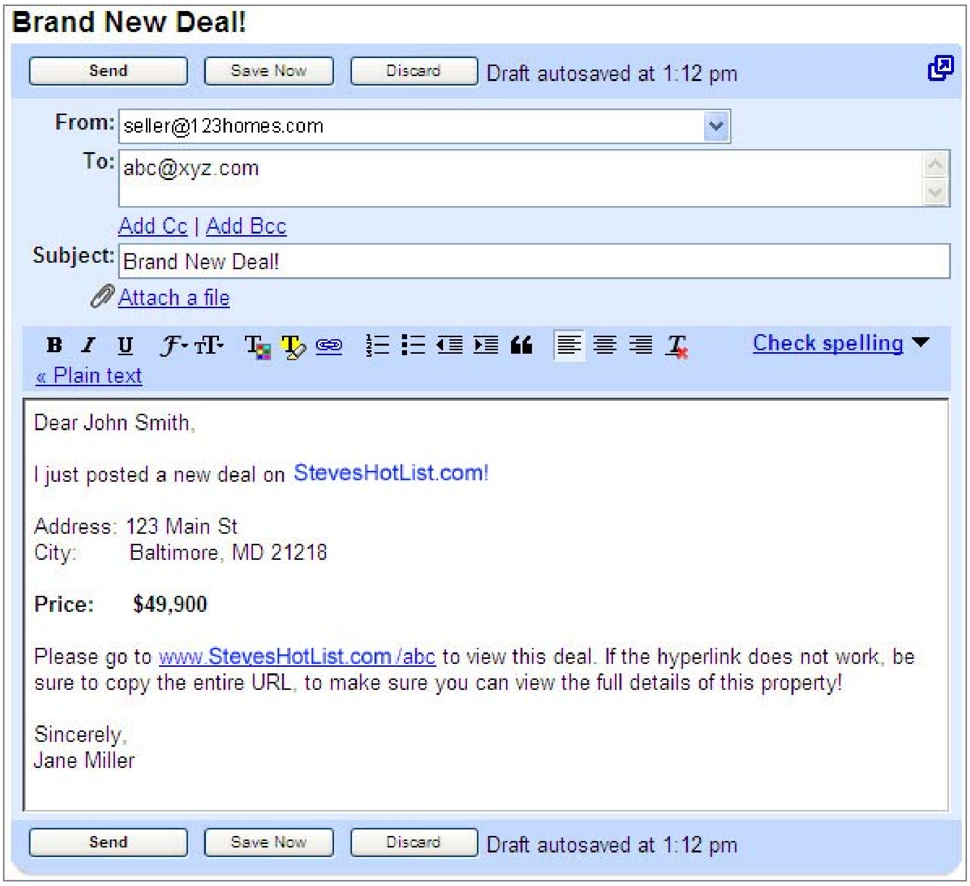


Figure 2.8: Example of email account with email advertisement.

was sent to all ARPANET addresses on the west coast of the United States of America. After that, many other services and corporations have used this strategy to advertise their products.

2.2.2 Banner Ads

As said above, the banner ad or web banner was invented in 1994 at HotWired. This form of advertising on the web is fed by an ad server, but in a similar manner to traditional ads it aims to notify and present a product or service to potential consumers in the attempt of convincing them to buy the product or service in question.

Typically, a banner ad is a small image that is tied to a target ad, i.e., a banner is a clickable ad. It may also include a number of other media elements (e.g., text slogan or audio message). It is tied to a hyperlink that points to a more detailed ad in order to convince the user about the virtues of a product or, simply, to disseminate information about a product or service. This means that the design and construction of a banner depends on the existing multimedia (e.g., JPEG format) and HTML technologies.

2.2.3 Pop-up Ads

A pop-up is an ad that is not requested (Figure 2.9). Pop-ups were made possible in 1995 -1996, when the Netscape Corporation came up with the Javascript language for web programming, in particular with the command named "window.open" which enables to open a new browser window. A pop-up is a non-requested browser window with ad content that may appear on user's compute device (e.g., desktop computer, smartphone, etc.) while the user surfs on the web.

Figure 2.9: Example of Pop-up.

The technologies behind pop-ups are the same as of the banners, that is, multimedia and HTML. Nevertheless, the pop-up windows are generated by a script (e.g., Javascript) injected into the HTML file. Patralli [Cha08] argues that the intrusive advertising formats like pop-ups are avoided by users, as they interrupt the browsing activity. Even worse, it is the fact that unsolicited pop-ups may take control over user's browser, stopping his/her browsing activities [New01] [Pal05].

In addition to pop-ups, there are also pop-unders and rollovers (also known as popovers or overlays). These latter ads have the same characteristics those of the typical pop-up. A pop-under distinguishes itself from a pop-up in that it is placed behind other windows, instead of being placed on front of them. A popover does not materialize as a window but as an image that has the quality of being automatically resized every time the mouse passes over it.

2.2.4 Rich Media Ads

The raise of the web programming languages (e.g., Javascript, Java and ActionScript) allowed for the development of a variety of creative and appealing ideas that web designers had in mind. Then, ads evolved towards dynamic ads, also called rich media ads. A rich media ad contains images (eventually animated sprites) or video and features some kind of user interaction. While the standard banners displayed only text and still images, the rich media ads are more dynamic; for example, we may have floating ads over the screen, size-variable ads over time, and even ads incorporating videos. Rich media ads reflect the development of web programming languages and HTML. As for Netscape's Javascript, Sun's Java was first released in 1995. Java allows for small executable programs (applets) that can run within web browsers. So, it was made possible to program ads as applets. Java started changing the face of the Internet advertising through the possibilities given by their interactive ad banners. These banners were prepared to let the users to introduce email addresses or other data chosen by the user, in order to personalize and deliver basic animations in the ads [YKS04]. ActionScript appeared in 1998, two years after the release of Macromedia's Flash. Again, the concept of animation was the leading idea of this language and software for the web. In 2001, Flash Player had possibly become the most distributed software on the Internet, ahead of giants like Internet Explorer, Netscape Navigator, and Real Player [Gay07]. In short, the web tools evolved

Figure 2.10: Example of a floating ad.

to that we call DHTML. DHTML is not a separate language on its own, but a combination of languages like HyperText Markup Language (HTML), Cascading Style Sheets (CSS), JavaScript, and Document Object Module (DOM) that allow us to make up a DHTML script. This made possible the concept of layers, that is, the contents to be exhibited on the browser appear on top of each other. The Flash technology together DHTML also allowed the creation of floating ads in 2001 at EyeBlaster, which enabled to move contents on screen after clicking an ad banner or a button. This was quite revolutionary in advertising, as the ads started to ''come out" from their static space on the site. But, the appearance of HTML5 in the 2010 late marks ‘‘the beginning of the end" of the rich media ads.

2.3 Advertising Types

Advertising products and services across the web can be done using a number of compute devices, namely: desktops, laptops, tablets, and smart phones. What these compute devices have in common is that they are able to exhibit web pages (on their screen) and their elements of text, still images, and video. Therefore, the natural places for displaying ads are the following: ordinary web pages, mobile web pages, social web pages, digital game frames, and video frames. This leads us to what we call ordinary web advertising, search engine advertising, mobile advertising, social advertising, in-game advertising, and in-video advertising, respectively.

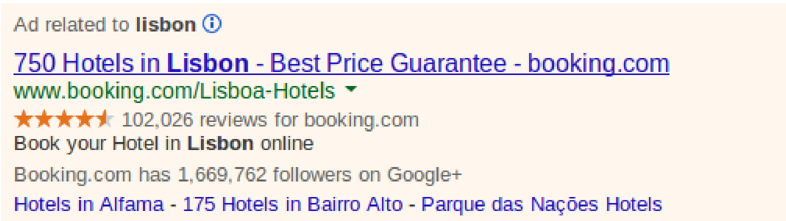


Figure 2.11: A snippet produced by Google search engine with keyword ‘‘Lisbon".

Ordinary web advertising is the most common type of advertising in most online web pages. The ordinary web pages work then as ad places. The ads present on web pages are normally displayed resorting to banners, pop-ups and rich media ads.

In *search engine advertising*, the ad places are also web pages, which exhibit rich snippets produced by the search engine (e.g., Google) as a result of a user search using keywords. Search engines like Google, Yahoo! and MSN use an auction mechanism to choose the ad that is then displayed alongside the search results, as shown in Figure 2.11.

Taking into consideration the size constraints of mobile phones, *mobile advertising* preferably makes usage of SMS (Short Message Service) or MMS (Multimedia Message Service), as illustrated in Figure 2.12. Similar to email ads, mobile ads may be also considered as spam (push advertising). However, a study conducted by Barwise *et al* [BS02] indicates that mobile ads can be well received if three conditions are met: first, the messages should be short, creative and with humor; second, they must be relevant to the receiver; and, at last, the receiver has previously given permission to receive advertising.

This type of advertising is gaining more and more importance because most of mobile phones and smartphones are connected to the internet, what makes it possible to obtain data about users and their locations, with the supplementary advantage that bluetooth protocol and GPS can be used too.

In *social advertising*, the ad places are user’s web pages of some social network (e.g., Facebook). A social ad incorporates the interactions that the user consents to be displayed and

Figure 2.12: Example of mobile advertisement.

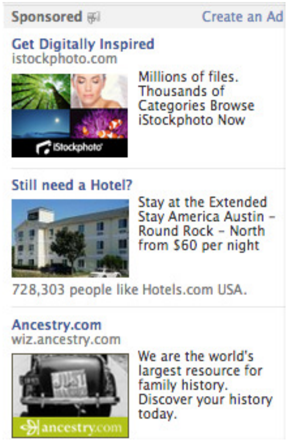


Figure 2.13: Example of advertisement in Facebook.

shared [Tay13], well as his/her photo and name, as illustrated in Figure 2.13. The social ads selection is made upon the underlying social network and the ad content is chosen depending on the data that belongs to the social relationship.

In-game advertising has been around for several years because video games have become a business of billions. In-game ad places are part of the scenery of game world, so we have only to put ads on them. The first in-game ads were static as they did not change over time because they were sticked on specific places at the programming level. Later on, dynamic in-game ads popped up in online games, which allow publishers to insert and remove ads anytime into and from games. That is, a chocolate vending machine in a game can be replaced by another vending machine of a different brand in the coming day.

In-video advertising is a trend that has emerged recently. In this case, ads are directly inserted in videos. In this case, the video frames themselves are the ad places. The main objective of this type of advertisement is to put an ad on a sequence of video frames in an automatic, non-intrusive manner, as necessary in, for example, broadcasting of soccer videos [XWBT05]. Finding non-intrusive regions in each video frame, which are supposed to be ad places, is a significant challenge because those regions change over time.

2.4 Algorithms for Ad Placement, Scheduling and Context

In the beginning of online advertising, when ads proliferated over the Internet, the reality was that sites were cluttered and ads were getting an overbearing representation on the screen, what was making a direct impact in the response and loading time of web pages [LS02]. Because the ads could not be displayed anywhere, it became clear that the ad place should be chosen carefully.

However, when a number of ad copies have to be displayed over a specific period of time, and normally there are more that one advertisement for each place, ad placement becomes not only a spatial problem, but also a scheduling (time) and context-aware problem (user and usage profiling). These three dimensions (*space*, *time* and *user*) have variable impact depending on the type of advertising.

2.4.1 Web page advertising

In web advertising, the ad placement and scheduling in web pages are two major problems in regards to the exhibition of ads. Recall that the six ad formats proposed by the Internet Advertising Bureau (IAB) in a way regulates how and where ads show up on a web page.

Adler et al[AGM02] introduced two NP-hard problems regarding ads schedule, the maxspace and minspace problems i.e., minimization and maximization problems. The maxspace problem aims to schedule ads in a way that the total space for slots (or places) is maximized, being assumed that the slots have a static capacity, while the ads may have different sizes and exhibition frequencies. The maxspace problem is based on the *cost per mille* (CPM) pricing model [Man04]. In this model the payment is done for each 1000 displayed ads, with a fixed fee that depends on factors like the time of day or type of the chosen websites. But, unlike the maxspace problem, the minspace tolerates dynamic sizes of the banner/time slot. This way, the idea is to minimize the tallest slot height for the ad scheduling. More specifically, Adler and colleagues proposed the Largest Size Least Full (LSLF) algorithm for solving the minspace problem and a LSLF-variant (called Subset-LSLF) to solve the maxspace problem. The LSLF algorithm sorts the ads by decreasing size, assigning then each ad to the least full slot. The Subset-LSLF algorithm classifies the ads into two subsets according to their size, computing then the subset with larger advertisement volume, after which the ads from the larger volume subset are assigned to the slots as long as there remains enough space. At last, the ads from the other subset are scheduled using the LSLF algorithm.

Dawande et al[DKS03] have suggested the introduction of new heuristic optimization techniques for both problems, minspace problem and maxspace problem. These two problems aim to find optimal solutions to the problem of scheduling ads that are competing for space on a web page over a planning horizon, say an hour. Note that one assumes all ads have the same width; in addition, all slots have the same width as the ads that they house because most web sites follow this ad presentation scheme. This means those two optimization problems have much to do with the height of ads. In fact, the objective of the minspace problem is to find a schedule with minimum height, but every single ad must appear at least once in a given time interval of the overall planning horizon. For the minspace problem, Dawande and colleagues presented an algorithm based on the Linear Programming Relaxation (LPR) with a Largest Frequency Least Full (LFLF) heuristic. The LFLF heuristic is similar to LSLF above, with the difference that the ads are now sorted in order to the decreasing show-up frequency. In regards to the maxspace problem, the objective is to find a feasible schedule of a proper subset of all ads such that the total weight of the scheduled ads is maximized; the weight of a schedule is the result of summing up the products of sizes by frequencies of its ads. The maxspace problem addresses the issue of selecting and placing ads in a manner that the advertisement provider profit is maximized. Later on, Dawande et al [DKS05] proposed another three LPR-based heuristics for the minspace problem, which constitute a slight improvement of their previous work [DKK^{+}00].

Freund and Naor [FN04] proposed additional heuristic-based solution techniques for those maxspace and minspace problems. In case of the minspace problem, they proposed the Smallest Size Least Full (SSLF) heuristic. In this approach the ads are sorted by increasing size. They combined the knapsack relaxation with their SSLF heuristic to solve the maxspace problem, while Menon and Amiri [MA04] used the Lagrangian relaxation to solve the maxspace problem.

Kumar et al [KJS06] also suggestted some techniques to solve the maxspace problem. They suggested the use of the Largest Size Most Full (LSMF) heuristic based on the multifit algorithm [CGJ78] in order to solve the bin packing problem.

Deane and Agarwal [DA12] proposed the use of a variable frequency for each ad, which changes its value for a given planning period. The purpose of this model is to give a bigger flexibility for publishers in their contracts and at same time increase the revenues.

2.4.2 Search Engine Advertising

Since the first search engines have become available, the advertising industry has explored this new data-sharing technology to perfect the success of ads . The advertiser specifies the keywords that should display their ads and the currency amount to pay per click. As said above, search engines like Google, Yahoo! and MSN use an auction mechanism to select the ad that ends up being displayed together with the search results (cf. Figure 2.11).

Tan and Srikant [TS12] proposed a stochastic model that describes the way that search service providers charge client companies for the ads by application of ad assignment strategies according to the queries inputted by users, which contain related keywords to the company. As the users search for keywords on a search engine, an additional advertising info may be displayed from companies that offer services or goods requested in the keywords form. The ads are displayed in specific web page places, called web page slots. They use a black-box approach, so that the idea is to use estimates in order to select an ad at every search query [TS12].

Given a specific search query, one of the problems of this approach lies in choosing the best algorithm to allocate a slot for an ad [MNS07]. Mehta et al[MSVV07] first introduced this matter as a generalization of the online matching problem. The search engine has information about the bids and the advertisers budgets. As the search query arrives with the correct keywords, the ad slot is allocated in order to maximize the revenues and respect the advertisers budget limitations.

Tan and Srikant[TS12] suggested an algorithm that performs well not only in the cases when the estimates are accurate, but also for the worst case. The experimental results obtained from 20 ads and 5000 queries, with uniform distribution over the bids and the keywords frequency, showed that the algorithm is better than the worst-case examples described in [MNS07].

Jiang et al [JLX+09] argued that an advertising platform is a critical component of the commercial search engines and proposed an image-based platform that allows the advertisers using search engines to bid on images, instead of plain text. This platform can be used for scenarios where images are the main input and includes an advertisement editorial tool that enables regions of interest (ROI) detection, image content understanding and matching modules. According to this platform the server hosts images that can be uploaded and bid by advertisers, while those image ads are displayed depending on the content of the images that the user browsed recently. In order to increase the ad relevance and delivery performance, a detection algorithm was implemented to find the ROI in images [JLX+09].

Dozens of different algorithms have been published in the last years for online keyword matching used in advertising, addressing problems such as the quality of query result, the bid limits from the companies, or revenue maximization (cf.[Meh12]).

2.4.3 Mobile Advertising

The user's dimension is predominant is mobile advertising. As said in a previous section, mobile advertising was initially based on SMS and MMS messages. But, two new types of mobile advertising arose with the boost of the mobile market, now known as push and pull advertising [HK02]. The *push* advertising aims to provide ads when the user does not expect them. On the other side, the *pull* advertising delivers ads that the user first started to looking for.

Almost every system of this sort uses what is called as location based services (LBS), which provide user's information about his/her current location. His/her location is obtained from Wifi, GPS or mobile stations. The user location allows for advertisers arrange a better advertising context for points of interest around the user, as it is the case of near shops, restaurants, and many other services that may be relevant to the user.

Yuan and Tsao [YT03] approached the problem of the relevance to the user through a two-level neural network for machine learning, neural network sensitivity analysis, and attribute-based filtering in order to relate the user's location with his/her learnt preferences through his/her browsing history, what has resulted in a recommendation mechanism that scores and ranks these two factors (user's preferences and browsing history), being so possible to display the top-N-scored ads.

Azni et al[HFT08] created a pull-based mobile advertising system. The system works in a master-slave symbiosis connected by bluetooth. The master sends a list of ads to the slave (user's phone) so that the user selects the one or more ads that he/she wants to see, the master responds by sending the selected ads. Although bluetooth has a short range, the ads are confined to the place where the user is. However, if the connection is established for a long time and has been be set to be always turned on, the user's phone will be more likely to be subject of spam.

Castro and Shimakawa [dCS06] proposed a method that personalizes mobile ads, by taking into account not only the user location, but also his/her interests. They implemented Concierge, a prototype system that was tested in a shopping environment. The work was focused on transferring from a push model to a pull model during the service period. First, the user receives a push ad, and then he/she can request an ad from a list to get more information of his/her interest (pull advertising). In order to prevent spam during the push phase, the contextual information of the user is calculated from his/her movement logs and is then properly used. This approach showed that the users react positively to pushed advertisements, as long as they are relevant according to their interests [dCS06].

Haddadi et al[HHB10] proposed the MobiAd, a push-based mobile advertising system. This system aggregates the data from user's smartphone, such as user profile, web history, browser cache, then relates this information with the ads that are selected from a pool of ads, and are broadcasted from the local mobile base station or from WiFi hotspots through a anonymous broadcast channel. These ads are stored in the smartphone for a period of time minimizing so the necessity to download the ads later on. The information about the ad views and clicks are then encrypted and reported with delay in order to minimize the possibility of such information being linked back to users.

In 2009, Kim et al[KLPC09] proposed a mobile advertising system (MAS), more specifically a push-based system. This system takes into account the different interests of the user along the day, so it aggregates the user's hit history hourly and his/her location, creating so a behavior profile of the user that is later related with his/her location, so that the system schedules the exhibition of ads according to such a profile. Similar systems and solutions for mobile advertising can also found in the works of Xu et al[XLL08], Gao and Ji [GJ08], LeMole et al[LNOS99], Liapis et al[LVY08], Kuo et al[KLW$^+$07] and Rashid et al[RCE05].

2.4.4 Social Media Advertising

In the 2011 comScore statistics (`http://www.comscore.com`), Facebook was the most attended website (20% of the entire time spent on the Internet), what is even more than search engines like Google and Yahoo! [Eld11]; hence, the interest of advertisers in social networks and communities.

In social networks (e.g., Facebook), one uses recommender systems to add context to ads, although these systems are common now in a variety of applications (e.g., music, books, search queries, and others) and products in general. A recommender system is a particular information filtering system that aims at predicting the "preference" that the user has for an item [AEK00] [SNC13].

The recommendation systems can be divided in three types: content-based filtering systems, collaborative filtering systems, and data mining-based systems. The *content-based filtering* [JZFF11], also referred to as cognitive filtering, recommends items (i.e., ads) to the user based on his/her preferences previously expressed in his/her profile. Therefore, a recommendation is done after determining a similarity-based matching between user profile items and content items existing in a document; the contents of each item is represented by a set of descriptors, which typically are the words in a document.

The *collaborative filtering* aims to study the preferences of other users in the social network in order to recommend an item to users in general [ERK10]. The information domain for a collaborative filtering system consists of users and their preferences for a variety of items. A user's preference for an item is called a rating, which is usually represented as a (user, item, rating) triple. The rating has a scale, which can be integer or floating point. A well-known scale is the binary scale (like/deslike) used in Facebook. This type of recommendation is commonly used in the recommendation systems because it is simple and effective [MR00] [Paz99] [Lam04].

Another recommendation approach consists in using *data mining techniques*. Lin et al [LAR00] proposed themselves to identify association rules between products and to use this association information to recommend items to the user. Herlocker and Konstan [HK01] used a similar approach to the one due to Lin and colleagues in order to recommend items that the user needs immediately to acquire, while Mobasher et al [MDLN02] extended this idea by recommending web pages according to the web pages associations present in the users web usage logs. For this purpose, Mobasher and colleagues check the similarity between the web pages recently visited by the user and the already collected data about the user profile.

Another important topic in social media is the banner placement problem, which was first described by Langheinrich et al[LNA+99]. As mentioned in a previous section, this problem has originated another problems such as over-targeting [Tom00], multi-impressions [NA05] [Nak02], and overselling [Nak02]. These targeted advertising techniques use the available data to segment user groups on the basis of ad preferences. This aims at making a decision about the place and time that the banner should be displayed across the social pages of users. Yang et al [YDCL06] used preference probabilities of user subgroups to schedule the exhibition of ads. These subgroups were identified through close relationships between their users, well as by their common interests [GT11].

2.4.5 In-Game Advertising

Today, digital games constitute one of the most profitable market in the world. In 2005, we could see that more people played games than used social networks [Cai05]. According to [Por11], the video games advertising revenues were evaluated in $1.9 billion dollars in 2010, with the fast growth in mobile games. This explains why many game titles are sponsored by brands, since they exhibit their ads during the development phase of the games. These ads are displayed on specific in-game places during the building up of scenes or their programming, that is, this is accomplished in a hard-coded basis, as it is the case of Pro Evolution Soccer 2014 (http://pes.konami.com) illustrated in Figure 2.14. This means that the game always displays the same ads in a particular sequence or context of the game [NKY04]. The hard coding approach is used due to the need of real-time in multiplayer online games (MOG). Online games require network capacity and dynamic ads would add more network data and therefore introduce further latency [CHL06] [CC06].

Chee et al[CLL+11] proposed a scalable advertisement approach for the image delivery mechanism using BitTorrent Peer-to-Peer (BT P2P) protocol that aims to achieve a scalable real-time delivery of advertisements. In this model each MOG player acts like a P2P node in the overall ad delivery system. This model seems to have a linear scalability, unlike the client-server model that features important scalability issues. The BT P2P model delivers online advertisement at a lower latency then the commonly used client-server model [CLL+11]. But, it is clear that this advertising area will evolve to dynamic ads in gaming in the near future.

2.4.6 In-Video Advertising

According to the IAB [Sil13b], in-video ads represent about now 7% of total profits in advertising, what translates into an increasing of 23% in regards to the figures of the previous year. In fact, in-video advertising is one of the trends that has emerged in recent years, and aims at inserting ads in a video automatically. This is essentially an ad placement problem because the main

Figure 2.14: Example hard coded in-game advertising from Pro Evolution Soccer 2014 (PES 2014).

question is ‘‘where?". That is, the ad placement is the dominant dimension in video. This is a difficult problem to solve in real-time because finding suited regions to place an ad has to be accomplished on a frame-to-frame basis over time.

Xu et al[XWBT05] developed a system that was able to insert an ad in broadcasted soccer videos, based on the detection of the static regions such as game timer, channel TV logo, central ellipse of the midfield, goal posts and the field lines, which result in non-intrusive regions to insert an ad in the broadcast videos. Soon after, they also developed a system Li et al[LWYX05] that was able to insert ads in real-time broadcasted videos of baseball matches. To insert the ad, they used a set of rules so that the proper location and timing of the ad were correct.

Three years late, Liu et al [LJHX08] designed a system called VCI (Virtual Content Insertion), which also enables the insertion of ads in video. They identified three problems that were solved by their system, namely when, where and how the advertisement should be placed in a video in a non-intrusive way. The problems of when and where were solved by means of the temporal and spatial attention analysis, that is, the system was able to detect that users attention changes over time and in space, and also to select the time that attracts more attention, in a space that attracts less.

Also in 2008, Chang et al [CHCW08] created a system for sports videos, in particular for tennis videos, called ViSA (Virtual Spotlight Advertising); cf. [CHCW10] for a follow-up of this system. This system incorporates the phycological effects of advertising to the consumer, having they used the AIDMA model, which represents the consumer response to advertisements in marketing communication. Based on this model, they defined three stages that were taken in consideration: recognition, affect and action. The system detects the court and player regions in the video, so that the region for ad inclusion can be determined (i.e., recognition stage). After that, each region is scored by its effectiveness so that the ad with the greatest score is chosen (i.e., affect stage). At last, the ad is placed in the region, being its colors then harmonized with the region’s colors where it will be placed (i.e., action stage) using the process described in [COSG$^+$06].

About 2007 to 2008, the ad context came to place as a new in-video advertising trend Mei et al[MHYL07] and [MHL08]. They developed two systems, called ImageSense and VideoSense, that were able to determine the most suitable regions in the image or video to insert ads. The regions are chosen on the basis of the saliency of the images, minimizing in this manner the intrusiveness of the ad, being the ad itself chosen from an ad repository according to its textual relevance expressed by its keywords, descriptions and transcripts of the web page where the video is inserted and visual concepts associated to the images and video. In 2008, Liao et al [LCH08] introduced a video-in-video system, called AdImage, that associates relevant ads by matching some invariant features in the images. These features are regions with high contrast, characteristic shape and texture, which are detected using Lowe's Difference of Gaussian and scale-invariant feature transform to represent these characteristics.

In 2010, Mei et al [MGHL10] created the AdOn. This in-video adversing system is also context-dependent. In order to insert relevant ads in a video, those researchers used an OCR algorithm to detect the text in the video, namely labels and subtitles, and used a vector space model as the basis of textual relevance between text, video, and ad. The region to place an ad is determined by extracting the keyframes, selecting then the one that is less intrusive by means of the detection of the foreground objects in the video.

2.5 User Profiling Algorithms

User profiling consists in creating a representation of an identity, interests, and geographical location of the user, being this data combined into personalized ads that appeal the user to the choosing of the announced products and services. As seen above, the user's dimension is a common denominator in all advertising types, although the in-game ads and in-video ads tend to be less interactive with the user in the sense that they are simply exposed to the user in visual terms. Ads should not be intrusive but appellative and, if possible, properly chosen towards the user. Nowadays, there are various approaches to gather information about the users interests. This information is made available by the user in an *explicit* manner or, alternatively, is gathered from user's behaviour in an *implicit* manner while he/she is interacting with some online environment (e.g., Facebook, Amazon, eBay, etc.). That is, the user shares this information with the advertiser, regardless of whether he/she is aware of it or not.

An example of *explicit user profiling* is the one described by Shannon et al in [SSQN09], who created an online advertising application that uses information gathered from a user's Facebook profile to target personalized ads to him/her. This application needs to be granted access to the Facebook information, such as age, gender, friends list, and relationships. This means that each user is given ads that are related to himself/herself and, possibly, to his/her shared interest group. However, not always the information explicitly provided by the user is accurate, purposely or not. For example, the user enters his/her profile by filling in specific forms in social networks such as LinkedIn and YouTube, but quite often such a information is incomplete or inconsistent, simply because the user is not willing to provide all of his/her data [TYZZ10].

This leads us to *implicit user profiling*, which allows us to glean information about the user based on his/her online actions and behaviour. For that purpose, one uses data mining, machine learning and other artificial intelligence techniques. An example is given by the Syskill & Webert software agent introduced by Pazzani et al [PMB96]; this agent learns to rate web pages, based on what it decides those pages that might interest to a user. This requires that the user first rates his/her visited pages on a three point scale. More specifically, Syskill & Webert is able to learn a separate profile for each topic of interest for each user, so that the user profile is seen as an aggregate of user's topic profiles.

Another example of implicit user profiling is due to Toubiana et al [TNB$^+$10], who proposed a practical architecture that allows to track users across web sites without compromising user privacy. In general terms, this technique is known as online behavioural advertising (OBA), and aims to infer user interests and preferences, which are then used to present personalized ads to the user. It is clear that OBA is not a new practice at all, because the third party DoubleClick's cookies have been around since the late 1990s. However, behavioural advertising has infringed on user privacy, what is seen as harmful by consumers and advocacy groups. Thus, the challenge is how to target ads to users without violating their privacy.

At last, the *hybrid user profiling* combines explicit and implicit user profiles [PCG03], as a way of targeting users with more accurate and personalized ads. In fact, nowadays profiling targeted advertising use both methods for ads personalization. Alt et al [ABK$^+$09] creates what they call as adaptive profiles, which means that the user profile is also determined by his/her online behaviour, mainly based on web pages that he/she explores. However, in order to create a richer profile, the user also allows other users to rank his/her own interests in different categories. [JBR11] also uses both approaches, using demographic features (e.g., age, gender, country, zip-code) and behavior features (page visits, clicked ads and search history) obtained by the click-logs of the user for building up a content-based ads matching system that relies not only on text matches between pages and ads, but also focus on the user.

Also most advertising methods based on profiles assume that a user has a single profile in a single location. However, Bilchev and Marston [BM03] had a different opinion, that a user has multiple profiles in a number of different locations held by service providers, and creates an overall user profile based on those, called distributed profile. To construct this overall profile, these multiple profiles are linked together instead of creating a single profile with a lot of data.

2.6 Discussion

The current sophistication of online advertising has much to do with the modern computing techniques, in particular those that have been developed for the Internet and web. Indeed, ad placement relates with optimization and geometry problems, ad scheduling is an optimization problem in computer science and operations research, while context-based problem solving has been around in artificial intelligence for many years.

Table 2.1 shows the more relevant developments in online advertising algorithms in the last ten to fifteen years. Interestingly, most advertising types (cf. second column of Table 2.1) have a static placement (cf. fourth column of Table 2.1) previously set up in the web pages, which can be explained by the need in keeping high speed rates in loading web pages. On the other hand, the dynamic ad placement (i.e., the ad placement is calculated on the fly) is most common in video, simply because it is quite difficult to know beforehand where the available regions are.

Table 2.1: Features of ad algorithms.

Authors	Type	Ad scheduling	Ad Placement	Ad context	Non-intrusiveness	Real-time
Lin et al [LAR00]	social	✗	static	user profiling	✓	✓
Mobasher et al [MDLN02]	social	✓	static	user profiling	✓	✓
Herlocker et al [HK01]	social	✓	static	user profiling	✓	✓
Adler et al [AGM02]	web	✓	static	--	✓	✗
[YT03]	mobile	✗	static	user profiling and location	✓	✓
Dawande et al [DKS03]	web	✓	static	--	✓	✗
Freund and Naor [FN04]	web	✓	static	--	✓	✗
Lam et al [Lam04]	social	✗	static	user profiling	✓	✓
Memom and Amiri [MA04]	web	✓	static	--	✓	✗
Xu et al [XWBT05]	in-video	✗	dynamic	user location	✓	-
Mehta et al [MSVV07]	search engine	✗	static	user profiling and location	✓	✓
Kumar et al [KJS06]	web	✓	static	--	✓	✗
Li et al[LWYX05]	in-video	✗	dynamic	user location	✓	✓
Dawande et al [DKS05]	web	✓	static	-	✓	✗
Haddadi et al [HHB10]	mobile	✗	static	user profiling and location	✗	✗
Yang et al [YDCL06]	social	✓	static	user profiling	✓	✓
Liu et al [LJHX08]	in-video	✗	dynamic	user location	✓	✗
Chang et al [CHCW08]	in-video	✗	dynamic	user location	✓	✗
Hua et al [HML08]	in-video	✗	dynamic	user profiling and location	✓	✗
Lisao et al [LCH08]	in-video	✗	static	user profiling	✗	✓
Kim et al [KLPC09]	mobile	✓	static	user profiling and location	✓	✓
Jiang et al [JLX^{+}09]	search engine	✗	static	user profiling and location	✓	✓
Mei et al [MGHL10]	in-video	✗	static	user profiling	✗	✓
Chee et al [CLL^{+}11]	in-game	✓	static	--	✓	✓
Tan and Skritant [TS12]	search engine	✗	static	user profiling and location	✓	✓
Deane et al [DA12]	web	✓	static	--	✓	✗

We also note that there is a real concern about the intrusiveness of ads (cf. sixth column of Table 2.1). Since the web pages have specific placements for advertising, it is in the interest of the users to not over-flood the web page with ads. In other words, ads must be the less intrusive as much as possible to the user, but, at the same time, it is necessary to maximize the number of ads to be displayed and consequently maximize the revenues, a problem that is addressed by the ad scheduling algorithms (cf. third column of Table 2.1). There is also the concern in designing and development of real-time ad algorithms (cf. seventh column of Table 2.1).

In respect to context-based inference (cf. fifth column of Table 2.1), we have identified three types of context: no context, location-based context, user-based context (i.e., user profiling), or both location and user-based context. In truth, context-based advertising has a great impact factor on appealing to the user, provided that it has to take in consideration user preferences and his/her geo-location.

Summing up, most ads are displayed in real-time, even having into consideration that the overhead incurred by scheduling, placement and context inference. Nevertheless, real-time rates are difficult to attain in-video advertising because a significant number of video frames have to be processed per second. Therefore, the focus has been the computation of non-intrusive video regions for ad placement, but recently a few solutions have appeared in the literature also addressing the context problems in video. One of the problems that has not been completely solved in in-video advertising is how to dynamically calculate the placement of ads in real-time video.

Chapter 3

Entropy-Based Advertising for Short Online Videos

This chapter describes an entropy-based algorithm for non-intrusiveness in-video advertising. At our best knowledge, there is no other algorithm that takes advantage of image entropy to in-video advertising. Besides we establish a comparison of our algorithm to Videosense algorithm [MHYL07], which can be considered as the state-of-art algorithm for in-video advertisement.

3.1 Introduction

There is a huge variety of online videos, as well as different genres of online videos, which can be categorized as comedy, sports, news, "howto", travels, music, films, animation, gadgets, games, people or animals [CDL08] [YQ]. Besides, each genre, spans videos with different durations, from a few seconds to a few hours.

In 2008, Xu Cheng et al. [CDL08] have analyzed more than 3 million videos acquired from *Youtube* for a period of 3 months in different categories and came to the conclusion that around 97.9% of the videos hosted in *Youtube* are smaller than 5 minutes. They also noted that the main categories of those videos were music and entertainment videos with 22.9% and 17.8%, respectively. In a more recent study conducted in 2011, Yang et al. [YQ] reinforced these statistics, with music and entertainment *Youtube* videos growing up to $\approx 50\%$ approximately in a universe of more than 400 million videos, having established that these two genres would continue to grow in the future.

Usually, the in-video advertising methods found in the literature cf. (Section 2.4.6) focus on specific genres, such as entertainment and sports (football and tennis videos). These videos have different durations, but are normally longer than $\approx 30-45$ minutes. However, as was stated above, these videos do not represent the reality of online videos. So, unlike other methods in the literature, this dissertation aims to conceive a method to insert advertisements in videos with around 5 minutes long, specially for the music and entertainment genres.

There are two research lines that are addressed in in-video advertising algorithm, the detection of the best placement and the contextualization of the advertising, (cf. Section 2.4.6). The first consists in developing algorithms capable of detecting the correct places placement in video, while the second relies on contextualization to insert ads in video. Note that, context has here to do with user profile.

As was already stated the focus of this thesis is on the first research line, that is, the objective is to create an algorithm capable of detecting the correct regions in video for advertising placement. The major concern when detecting regions for advertising placement resides in the *intrusiveness* of ads presented to the user. Advertising intrusiveness is normally associated with feelings of irritation [LEL02], the reason being that online advertisement is normally unwanted by the user, with messages that are both unappealing and disrupting when the ad is displayed..

When doing in-video advertising, intrusiveness mainly arises from three sources, the location (*where*) and the timing (*when*) chosen for ad insertion in the video, but also from the way ads are displayed (*how*) (e.g., size, number and so forth). These three problems are the ones the proposed algorithm has to be able to solve.

To solve the problem of advertisement placement (*where*) the algorithm needs to be able to insert content without occluding any relevant objects in the scene, so that the advertisement does not disturb the video watching. It is needed to take into account the time period that the advertisement needs to stay on screen so that the viewer can absorb its message. In other words, we need to determine not only the minimum time of advertising display, but also its maximum time, so that the viewer does not feel the desire to skip it or change the video. For the *how* problem, the main concern is related to the size and number of ads inserted in the video. Note that the viewing of a video would become unbearable if the video was flooded with ads. Another important aspect that can also be studied, is the way an ad is displayed overtime. In fact, when an ad is inserted it is recommendable that it does not vary to much from the place to another, in order to minimize the disturbance to the viewer.

3.2 Algorithm Overview

The in-video ad placement algorithm proposed in this chapter (and also in this dissertation) can be divided in five main steps:

1. Preprocessing.
2. Uniform region detection.
3. Spatial analysis.
4. Temporal analysis.
5. Ad placement.

These five steps have been designed to detect advertising regions in video, but also solve the problems (*where, when, how*) mentioned above. We utilize preprocessing techniques do remove the noise and lighting. This is followed by the application of Shannon's entropy combined with Otsu's threshold, what enables the detection of all scene objects present in video. From these objects, a quadtree is then constructed for each video frame in a dynamic manner, leading to a set of available regions for placement of ads. The final decision about placement is then taken after performing temporal analysis of the video and its available regions over time.

3.3 Preprocessing

In image processing and analysis, preprocessing consists of a set of operations that are applied to data before doing anything else. This stage is important because has a direct impact on the results produced in subsequent steps. The main goal is to remove noise as much as possible from the video frames, including shadows and reflections.

As shown in Algorithm 1, the preprocessing step of the proposed algorithm can be divided in the following sub-steps:

1. *Frame extraction and frame resize* (lines 3-5 in Alg 1).

2. *Gaussian blurring* (line 7 in Alg 1).

3. *RGB-to-HSV Conversion* (line 8 in Alg 1).

Algorithm 1 Preprocessing step

Input:
aVideo ▷ video that will be processed

1: **procedure** Videopreprocessing($aVideo$)
2: **while** $!endofvideo$ **do**
3: $RGBframe \leftarrow$ GrabFrame($aVideo$) ▷ get video frame
4: **if** $RGBframe.resolution > MaximumResolution$ **then**
5: $RGBframe \leftarrow$Resize($RGBframe$, $MaximumResolution$)
6: **end if**
7: $RGBframe \leftarrow$GaussianBlur($RGBframe$, $KernelWindow$, σ)
8: $HSVframe \leftarrow$ConvertRGBToHSV($RGBframe$)
9: **end while**
10: **end procedure**

3.3.1 Frame extraction and frame resize

This sub-step aims to extract each video frame, changing its resolution to a smaller one, in order to speed up the application of subsequent operations. Note that maximum resolution was 640x480 (line 4 in Alg 1). The lower the resolution of an image, the faster will be the application of such operators, more specifically the operators used in uniform region detection step. However, with less resolution there will also be a higher loss of data from the image.

3.3.2 Gaussian Blurring

2-D Gaussian blur operations are normally used in image processing to reduce the noise detail and artefacts from an image. Gaussian blur consists in convolving each pixel of an image with a Gaussian kernel, being the intensity of output pixel the result of weighted average of the applied convolution. The Gaussian kernel coefficients are calculated using the Eq. (3.1), where x and y represents the pixel position in horizontal and vertical axis respectively, and σ represents the standard deviation of the Gaussian distribution. It is generally assumed that the distribution has a mean of zero ($\mu = 0$) and needs to be discretized in order to be applied to the discrete pixels, as illustrated in Figure 3.1.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{3.1}$$

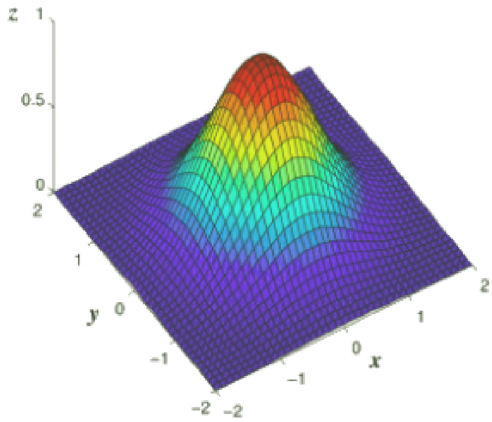


Figure 3.1: 3-D representation of a Gaussian distribution with $\mu = 0$ and $\sigma = 1$.

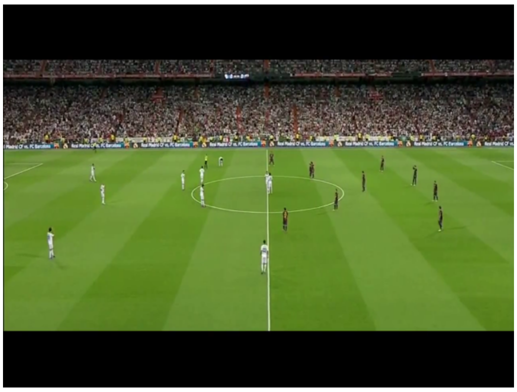
As it can be seen from Eq. (3.2), the values of the kernel coefficients are smaller as the distance to the kernel center increases, which means that central pixels of the kernel window will have a higher weight that those further away.

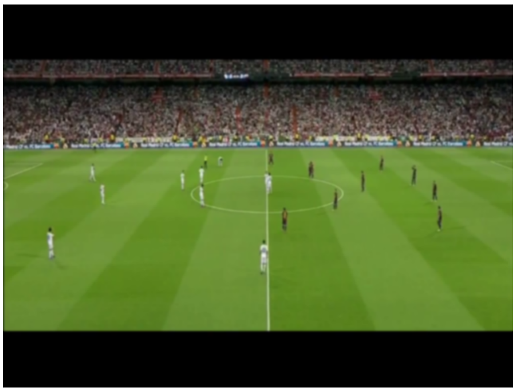
$$G = \frac{1}{273} \begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 5 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix} \tag{3.2}$$

There are two parameters that have a direct impact on the performance of the Gaussian blur operator. The first is the value of the standard deviation σ, so that the higher the standard deviation value, the higher the level of smoothing will be applied, as illustrated in Figure 3.2. The second parameter is the size of the kernel window (lines 7 in Alg 1). The size of the kernel window also has an impact on the performance of the Gaussian blur operator, specially on the speed of the blurring operation, so that the bigger the kernel size, the longer in time is the blurring operation.

3.3.3 RGB-to-HSV Conversion

A color space is a measuring system for colors that can be perceived by humans [IHKM12]. RGB color space is the most commonly used color space in displaying color devices. RGB color space is an additive space that uses the three primitive colors: red, green and blue. These colors are then combined in order to reproduce all the colors of the RGB color space. Although RGB is a good color space for color displaying, it is not however efficient in image processing, operations such as color segmentation and analysis, largely because of the correlation between the R, G and B components [LR97]. For example, when a color changes all three components will also change.





(a) (b)

(c)

Figure 3.2: Example of applying a Gaussian blur. (a) Original image. (b) Image with standard deviation $\sigma = 1$. (c) Image with standard deviation $\sigma = 5$.

One of the major problems present in most images and that almost every image processing algorithm has to do with the lighting changes and shadow effects. These effects will appear in the image as artefacts, which will have a negative impact when finding large uniform regions (i.e., regions without scene objects).

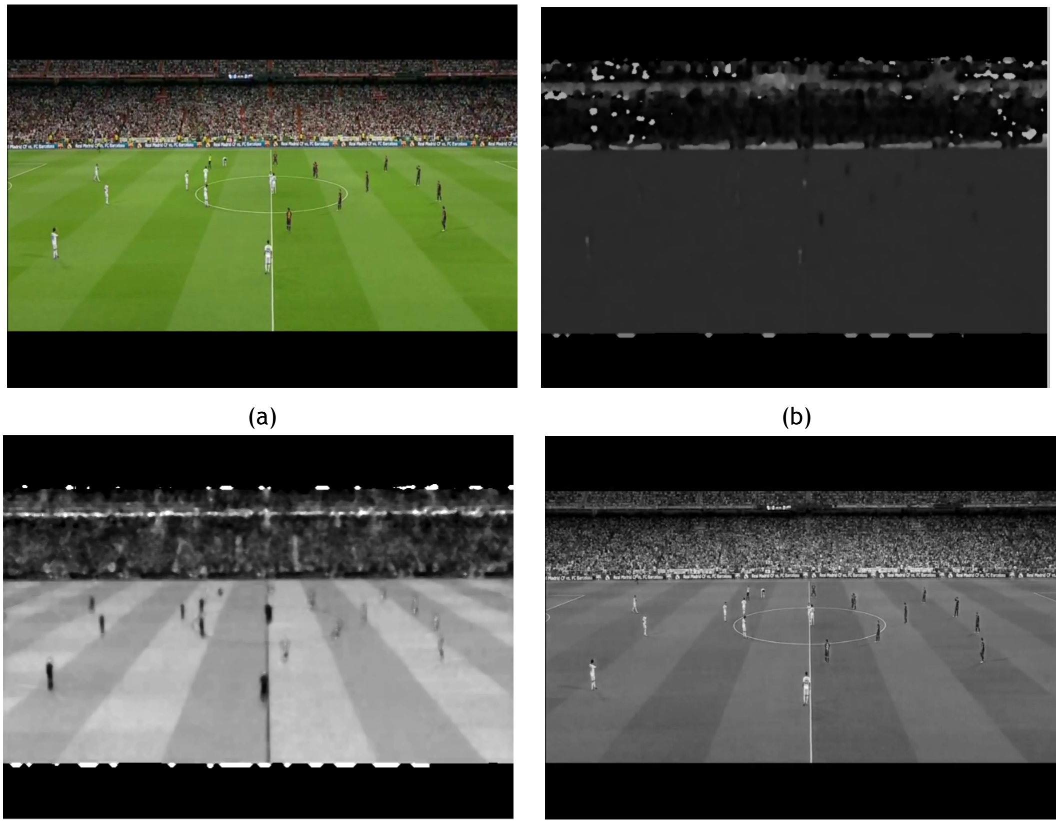
When using RGB color space, is very difficult to remove these lighting and shadow features from an image because of the correlation already mentioned above. In order to overcame these problems, it is usual custom proceed to change to a color space, that is able to attenuate the mentioned effects.

Such a color space is the HSV, which seemingly provides a more intuitive perception of color to us [HS02]. Besides, HSV color space is also considered to be a better choice for image processing since the difference between two colors is similar to the difference perceived by humans.

HSV color space is composed of three components: hue (H), saturation (S) and value (V) . The hue component represents the color and varies in the angular interval of $[0°, 360°]$; the saturation component establishes the depth or purity of the color and is normally represented in the interval $[0, 255]$; the value component defines the intensity of each color, also represented in a interval between $[0, 255]$ [SQP02].

In the proposed algorithm, one are converts from RGB to HSV color space, because it becomes possible to separate the *luminance* (image intensity that is represented by the value component) from the *chrominance*, which corresponds to both hue and saturation components. Let us consider the example in Figure 3.3. The predominant color in Figure 3.3(a) is the one concerning the football pitch, which has different green colors in it, the darker and lighter green stripes. To extract this green pitch using color threshold in RGB color space, it would be difficult to establish a linear range between all the greens present in the image. It is easier to do it using HSV, since the hue component (Figure 3.3(b)) represents all greens in a continuous angular interval.

Besides, there is also the problem of the lighting effects of the video frames, which are mainly represented by the value component of the HSV color space, making it possible to properly correct them.



(a) (b) (c) (d)

Figure 3.3: HSV color representation: (a) original image; (b) hue component; (c) saturation component; (d) value component

As known, in order to convert the RGB color space to the HSV color space it is needed to use the following Eqs. (3.3), (3.4) and (3.5) [CSX07]:.

$$H = 60^\circ * \begin{cases} 0 & \text{if } \max(R,G,B) = \min(R,G,B) \\ \frac{G-B}{\max(R,G,B)-\min(R,G,B)} \bmod 360^\circ & \text{if } \max(R,G,B) = R \\ \frac{B-R}{\max(R,G,B)-\min(R,G,B)} + 120^\circ & \text{if } \max(R,G,B) = G \\ \frac{R-G}{\max(R,G,B)-\min(R,G,B)} + 240^\circ & \text{if } \max(R,G,B) = B \end{cases} \tag{3.3}$$

and

$$S = \begin{cases} \frac{\max(R,G,B) - \min(R,G,B)}{\max(R,G,B)} & \text{if } \max(R,G,B) \neq 0 \\ 0 & \text{if otherwise} \end{cases} \tag{3.4}$$

and

$$V = \max(R,G,B) \tag{3.5}$$

3.4 Uniform region detection

The uniform region detection step aims to separate the background regions such as sky, field court or walls, from the foreground regions such as people or any other object that could be relevant. The process is described in Alg. 2 and can be divided into the following two sub-steps:

1. *Shannon entropy* (lines 2 to 17 in Alg.2).

2. *Otsu's threshold* (line 18 in Alg.2).

Algorithm 2 Uniform region detection step

Input:
HSVImageComponent ▷ Matrix with a HSV color space component

Output:
HSVEntropyComponent ▷ Frame that contains uniform regions in white other objects in black

```
 1: procedure RegionDetection(HSVImageComponent)
 2:     for all HSVImageComponent.rows do
 3:         for all HSVImageComponent.columns do
 4:             int histogram[256]              ▷ histogram array, all values initialized as 0
 5:             for l=-2 : 2 do                 ▷ Neighbourhood of 5-by-5
 6:                 for k=-2 : 2 do
 7:                     value ← HSVImageComponent[i + l][j + c]
 8:                     histogram[value] += 1
 9:                 end for
10:             end for
11:             for all histogram[value] ≠ 0 do
12:                 prob = histogram[value] / N              ▷ N= 5x5 Eq. (3.7)
13:                 entropy = prob.ln(prob)                  ▷ Eq. (3.8)
14:             end for
15:             HSVEntropyComponent[i][j] ← −entropy
16:         end for
17:     end for
18:     HSVEntropyComponent ← OtsuThreshold(HSVEntropyComponent)
19:     return HSVEntropyComponent
20: end procedure
```

3.4.1 Shannon Entropy

Entropy is normally defined as the measure of disorder of a system. In 1948, Shannon redefined this concept, as the measure of the uncertainty in an information system [Sha01]. Shannon's entropy states that the information content of a discrete random variable X that has a probability distribution $p_i = (p_1, ..., p_k)$ is defined as :

$$H(X) = -\sum_{i=1,...,k} p_i \ln p_i. \tag{3.6}$$

In image processing, we can also adopt Shannon's concept of entropy. In this case, entropy can be defined as a measure of color distribution in the image histogram. In other words the entropy H of image X can be calculated using Eq.(3.6), where $p_i = (p_1, ..., p_k)$ represents the probability distribution of the k intensity levels of the image histogram [PP93].

In the proposed algorithm, the entropy of each pixel is defined by the intensity level distribution of the histogram of a neighbourhood N centered at such pixel of the image. The more disperse the histogram, the higher is the entropy. Consequently, a histogram having only one intensity level means that the image entropy is 0.

Let I be a grayscale image. The probability p_i of a intensity level i is present in our neighbourhood is given as the number of occurrences n of this intensity in a neighbourhood N (e.g., 5x5) in the image I, as follows:

$$p_x = \frac{n}{N} \tag{3.7}$$

Taking Eq. (3.6) into consideration, the entropy H of a pixel $I(r, c)$ could be described as follows:

$$H(I(r, c)) = -\sum_{i=1}^{k} \left(\frac{n}{N}\right) \ln \left(\frac{n}{N}\right) \tag{3.8}$$

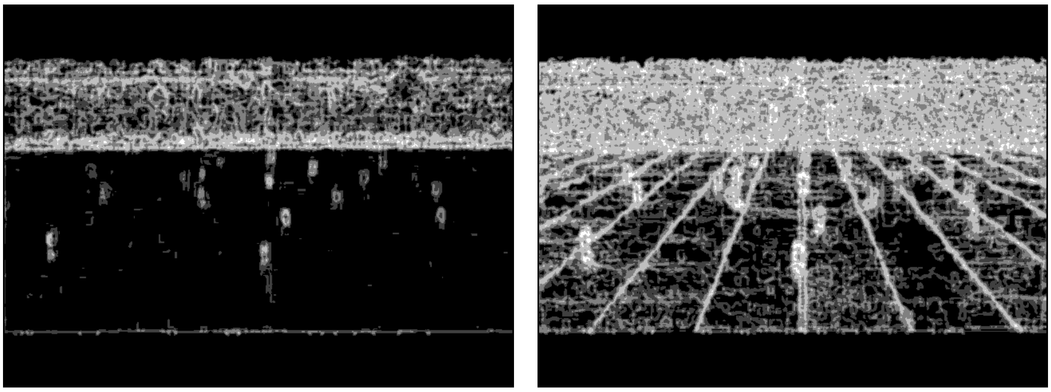
where k is the number of different grayscale intensities present in our neighbourhood, as illustrated in lines 2 to 17 of Alg. 2.

We calculate the entropy given by Eq. (3.8) for two images, the images that represent the hue component H and the saturation S, as those shown in Figures 3.3(b) and 3.3(c), resulting in two new images H' and S', respectively, where each pixel represents the entropy of the pixel in the images H and S, as illustrated in Figure 3.4. The value component is not used, because as mentioned above, the V component of the HSV may cause noise in the detection of advertising regions, resulting in regions wrongly classified as scene objects.

3.4.2 Otsu's Threshold

We use Otsu's thresholding to automatically separate the uniform regions of a image from the scene objects, as described in [Ots75]. Otsu's thresholding assumes a bimodal distribution of the intensity values. In other words, it is assumed that the histogram of the image has two main classes (normally for foreground and background objects). Otsu's technique selects the threshold value that separates these two classes of pixels by minimizing the variance within each class.

For that purpose, we first calculate the entropy images (i.e., those featuring the entropy



(a) (b)

Figure 3.4: Images resulting from applying Shannon's entropy to hue (a) and saturation (b) components.

of each pixel) H' and S'. This images follows a bimodal distribution where uniform regions correspond to pixels with low entropy value, and scene objects correspond to pixels with high entropy values.

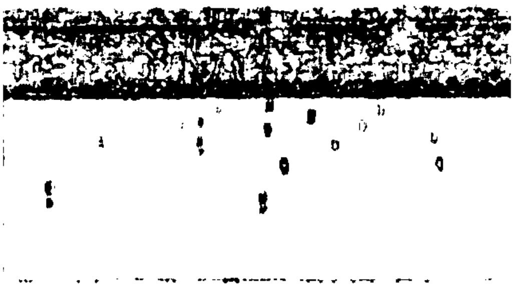
Otsu's threshold is applied to both H' and S' separating the color uniform regions from the objects of the scene. With this in mind, each pixel of uniform regions is set to the binary value 1 while the remaining pixels will take the binary value 0, as illustrated in Figures 3.5(a) and 3.5(b). Having these two binary images, it remains to merge these images into a single image, using the binary operator OR. The result of the operator OR is 1 if at least one of the bits is is 1; otherwise, the result will be 0. In other words, only if of H' and its homologous pixel of S' 0 the final image will be considered as a pixel of a as scene object; otherwise the pixels will be considered as uniform regions, ie, they are set to 1. This method is applied is described in [Ots75] and corresponds to line 18 of Alg. 2 .

3.5 Spatial Analysis

The spatial analysis of an image serves the purpose of determining all the available regions for advertising placement. This analysis takes the Otsu image calculated in the previous stage as input (cf. Figure 3.5(c)). In Figure 3.5(c), white regions are those available for ad placement, whereas regions in black feature the objects in the scene. Notice that these objects cannot be occluded by the advertisement in order to prevent intrusiveness as much as possible.

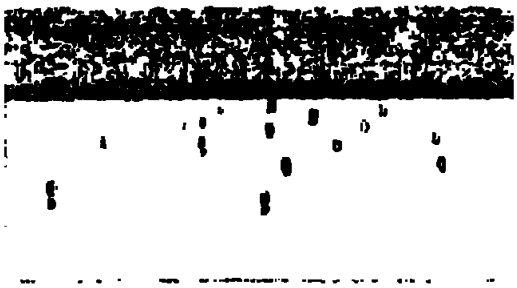
The spatial analysis of an image starts with the generation of the negative of the Otsu image. Because some noise may still remain from the previous stage, the morphological erosion operator is applied to such a negative image, allowing us to remove this noise, as well as reduce the number of pixels representing the scene objects without destroying their structure. The idea of this cleaning-up operation is to prevent the redundant fragmentation of the quadtree that comes afterwards. In fact, we use a point quadtree data structure [Sam06] to determine those available region, in each video frame, from the scene objects presented in the image.

A quadtree data structure is a way of partitioning a 2D region into four quadrants recursively. There are two main methods for quadtrees: region quadtree and point quadtree. The region



(a) Result of applying Shannon's entropy and Otsu's threshold to Hue component.

(b) Result of applying Shannon's entropy and Otsu's threshold to Saturation component.



(c) Result of OR operator between the images (a) and (b).

Figure 3.5: Steps of uniform region detection stage.

quadtree divides a region into four equally-sized quadrants in a recursive manner, while a point quadtree divides a region into four quadrangles that are not necessarily of the same size. That is, a point quadtree adapts easily to the contents of an image because the division is accomplished with reference to a meaningful point (belonging to an object) of the image. Furthermore, note that each point represents part of a scene object and we want regions without any object point inside it, being so possible to insert some advertisement in those object-free regions.

The quadtree subdivision procedure is detailed in Alg.3, which has the following stopping conditions:

1. There is not any objects points inside a region (lines 2 and 13 in Alg. 3).

2. The size of the region, both in width or height, is smaller than the size of the advertisement to be inserted (line 11 in Alg. 3).

The chosen point to serve as root for subdivision is the closest object point to the center of the region (line 5 in Alg. 3). As it can be seen in Figure 3.6(b), the red dots are the points chosen for region division. The order for the image spatial division is green, yellow, blue, and then pink. When the two conditions above are met, the spatial division terminates. The next step is to select all the empty regions in the quadtree (all regions where there are no points). From which we filter out those regions that have larger size than the advertisement to be inserted (line 14

Algorithm 3 Quadtree generation algorithm

Input:

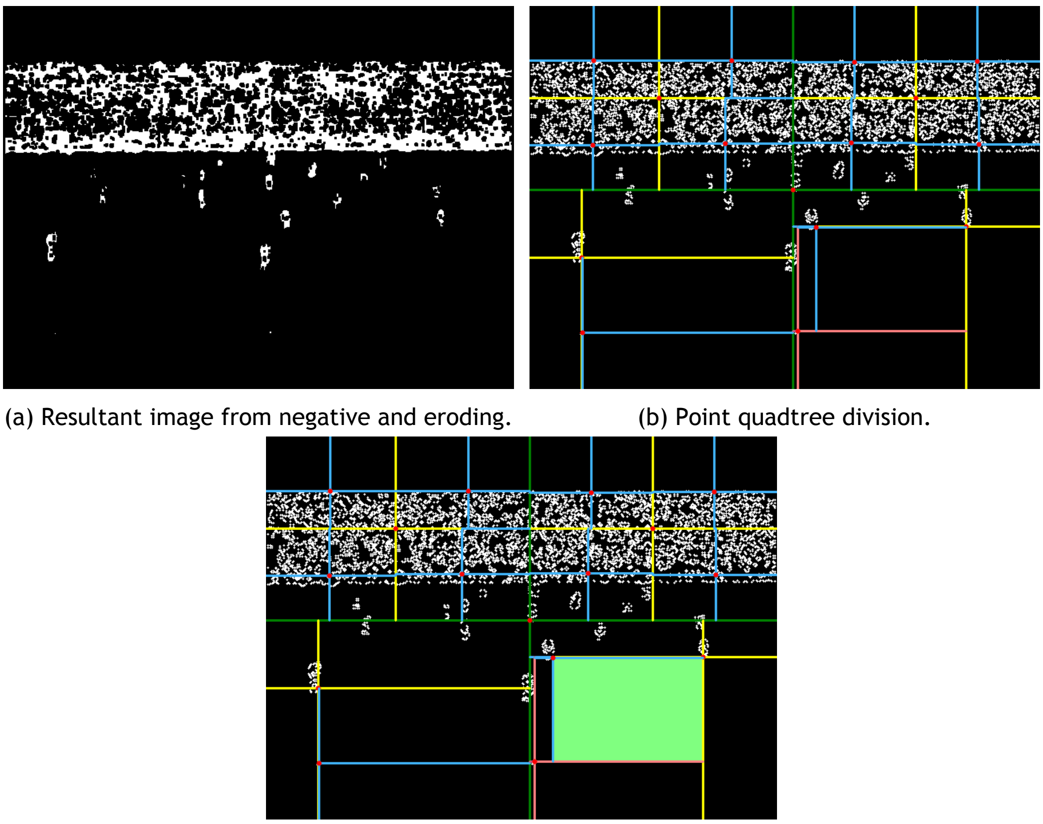
R ▷ root region

Output:

RegionVector: ▷ vector that contains all available spots

procedure QuadTreeSubDivision(R) ▷ Recursive function
    if $R.empty()$ **then**
        return
    end if
    $C \leftarrow$ GetClosestCenterPoint(R) ▷ return closest point to region center
    for k = 1 : 4 **do** ▷ Initiate subdivision process, for each quadrant
        $R->Q_k$ = CalculateNewRegion(C, R) ▷ Calculate new sub-region
        DistributePoints($R->Q_k, R->Points$) ▷ Distribute points between new quadrants
        if CheckQuadrantDimension($R->Q_k$) $== true$ **then**
            if $R->Q_k.empty() == true$ **then**
                $RegionVector \leftarrow$ NewRegion($R->Q_k$)
            else
                QuadTreeSubDivision($R->Q_k$)
            end if
        end if
    end for
    return
end procedure

in Alg.3). These latter regions are marked as potential regions for advertising placement in the next stage of the algorithm (Figure 3.6(c)).



(a) Resultant image from negative and eroding.

(b) Point quadtree division.

(c) Possible spot for advertisement insertion.

Figure 3.6: Steps of spatial analysis stage.

3.6 Temporal Analysis

Calculated the available empty regions in each frame, it is now time to determine the final regions for ad placement. This final regions are chosen according to the both position and period of time in video. From spatial analysis step we have stored the possible regions for ad placement but also the scene objects of the frames, and are now used in this step. The temporal analysis step can be divided in three sub-steps:

1. Block creation.
2. Block Merging.
3. Timeline creation.

3.6.1 Block creation

In temporal analysis step, we conceive what we call a *block*. A block, can be described as a recorded region over time. In $C++$ is a data structure that stores the data of an available region, and the corresponding frames were the advertisement could be inserted. The block creation is detailed in Alg.4.

Taking into account that from frame to frame, motion occurs in the video, it is not possible to have the same regions available for extended periods of time, so, each empty region is tested for the follow up frames.

Algorithm 4 Block Creation

Input:
RegionVector ▷ vector that contains all available regions

output:
DetectedBlocks ▷ vector that contains all detected blocks

1: **procedure** CreateBlock($RegionVector$)
2:     **for** i=0 : RegionVector.Size() **do** ▷ For each detected region
3:         $R \leftarrow RegionVector[i]$
4:         $C \leftarrow R.centroid$
5:         $block \leftarrow$CreateBlock(R);
6:         **for** frame=$R.frame$: endofframes **do**
7:             **if** CheckRegion(C) **then** ▷ check if region is not available in that frame
8:                 $block->end = frame$
9:                 $DetectedBlocks \leftarrow block$;
10:                 break
11:             **end if**
12:         **end for**
13:     **end for**
14: **end procedure**

Starting with the first frame, we pick one of the regions calculated in the previous step and calculate its centroid, (line 3 and 4 in Alg.4). We use this centroid as the corresponding center were advertisement should be inserted. Having all the scene objects positions calculated from quadtree construction, we calculate the distance between the region centroid and the position of scene objects for the follow-up frames. If this distance is less than a threshold (corresponding to the size of advertisement), such region can not host advertisement after that respective frame (line 7 in Alg.4), in other words the construction of this block is ended (line 8 in Alg.4), being stored in a vector of blocks (line 9 in Alg.4).

3.6.2 Block merging

The block merging step can be divided in two phases as seen in Alg. 5. The first phase consists in merging all blocks that overlap partially or completely over a time period corresponding to a set of frames (line 2 to 10 in Alg.4). The second phase consists in merging blocks that remain at the same position, but due to artefacts momentarily disappear between frames.

All the detected blocks found in the previous sub-step are compared to the other detected blocks (line 2 in Alg.5). If the distance between the two detected blocks is less than $1/4$ of the size of the diameter of the advertisement and one of them overlap partially or completely the other, instead of maintain these two blocks, (line 8 in Alg.4) we merge as one (line 7 in Alg.4).

One of the major problems in image processing is to completely separate the foreground from the background objects, in an automatic manner. In fact, some artefacts will remain, even after the uniform region detection stage. Such artefacts will undermine the effectiveness of the construction of blocks, reducing the number of frames where each region is available.

The second phase is to mitigate this problem. The detected blocks stored from the first phase will be compared to each other, if the time difference between the last frame of block A and the first frame of block B is less than one second (line 16 in Alg.5) and the Euclidean distance between the corresponding center position of block A and B is inside the threshold, $1/4$ of the size of the diameter of the advertisement, (line 18 in Alg.5), then these two blocks will also be merged in a bigger block (line 21 in Alg.5), the data from B is inserted in Block A and Block B is deleted (line 22 in Alg.5), otherwise both blocks stay as they were.

3.6.3 Timeline creation

The blocks determined above will be sorted in decreasing order of their time duration. At this point, we will have two options. The first option is to allow only one ad in the video, while the second option is to insert multiple ads in the video.

In case of the first option, we just need to add the ad to the free region corresponding to the longest block over time.

Figure 3.7: Timeline block separation.

The second option is to allow multiple ads along the course of the video. In this case, we will also start the operation by choosing the longest blocks, and will continuously enter these blocks on the timeline. If a period of the timeline is already occupied by a block A, block B will be split in two parts, the matching part will be removed from the block while the second part of

Algorithm 5 Block Merging

```
Input:
DetectedBlocks     ▷ vector that contains all the detected blocks
T     ▷ value that corresponds to the number a number of frames for time merging
D     ▷ value that corresponds to the maximum distance between two centroids
output:
BlockVector     ▷ vector that contains all merged blocks
procedure MergeBlocks(SpotVector)
    for all Detected blocks do
        Block b ← DetectedBlock.at(i)
        index = CheckForCloseBlock(b, D)     ▷ returns index block position if exists
        if index ≠ −1 then
            MergeBlock(b, index)     ▷ merge blocks
        else
            BlockVector ← AddBlockToVector(b)
        end if
    end for

    for i = 0 : BlockVector.Size()-1 do     ▷ For each available block
        Block A = BlockVector.at(i)
        Block B = BlockVector.at(i + 1)
            ▷ determine the time diference between the lasframe of A and firstframe of B
        diff = TimeDifference(B, A);
            ▷ determine the euclidean distance between the lasframe of A and firstframe of B
        distance = CalculateDistance(B, A)
        if diff < T then
            if distance < D then
                Merge(A, B);     ▷ Update block A, adding B data to the block A
                DeleteBlock(B);     ▷ Delete block B
            end if
        end if
    end for
end procedure
```

block B will once again be added to the sorted list as shown in Figure 3.7. This procedure ends when all blocks bigger than a minimum time period are used or the maximum advertisement time is used.

3.7 Non-intrusive Ad Placement

In the previous sections (spatial and temporal analysis), it was possible to solve the problems of "where" and "when" the advertisement should be inserted. The only problem that remains unsolved is the "how" the advertisement should be inserted. Ad placement should be performed in a non-intrusive manner. If the advertisement is inserted bluntly on the video frames it may cause some discomfort to the user. In order to reduce this negative impact for the user some blending techniques are applied.

There are many ways to blend two images. In the work of Chang et al. [CHCW08], they solve this exact problem using color harmonization [COSG$^+$06]. But this is not the only way to blend two images. One of those is using the functions inherent to Adobe Photoshop blending modes [pho00]. The mathematical functions of these blending modes (*add, multiply, overlay, darken,* *burn, hue shift and screen*)as been implemented and added to the our algorithm.

(a) Normal. (b) Add.

(c) Multiply (d) Screen.

(e) Darken. (f) Burn.

(g) Hue shift. (h) OverLay.

Figure 3.8: Ad insertion, blending functions.

Let us denote I as the output image, b as the background pixel of the Figure 3.3(a) and f as the foreground pixel of *Coca-Cola* logo. In Figure 3.8, we see the results of applying a number of blending modes to the Coca-Cola advertisement:

- **Normal.** This is the default mode or the basic blending mode where the pixels in the background image are replaced by the pixels of the foreground image. Mathematically would be $I(b, f) = f$. In this case, the advertisement is inserted bluntly as seen in Figure 3.8(a).

- **Add** is one of the most used blending modes, $I(b, f, x) = f.x + b.(1 - x)$, where x is a real number between $[0 - 1]$. The result is the effect of transparency (Figure 3.8(b)).

- **Multiply.** This mode consists in multiplying the background pixels with the foreground pixels, $I(b, f) = b.f$ the result image is always a darker as one of the blended images. While when multiplying background pixel with a white freground the result will be equal to the background color as it can be seen in Figure 3.8(c).

- **Screen** This mode consists in adding the colors of the background and foreground and subtract its product, as described in the formula $I(b, f) = b + f - (b.f)$. The resulting color is always a lighter color as shown in Figure 3.8(d).

- **Darken.** It always selects the darkest color of the background or foreground, $I(b, f) = \text{min}(b, f)$ (Figure 3.8(e)).

- **Burn.** It darkens the background color reflecting the color of the foreground increasing the contrast between the two, (Figure 3.8(f)).

$$I(b, f) = \begin{cases} 1 - (\text{min}(1, (1 - b)/f)) & \text{if } f \neq 0 \\ 0 & \text{if } f = 0 \end{cases}$$

- **Hue Shift.** It is applied in HSV color space. It preserves the saturation and value components of the background color and shifts the hue component of the foreground towards the background hue component, as shown in Figure 3.8(g).

- **Overlay** This mode consists in multiplying or screening the colors, depending on the color of the foreground. It preserves the lights and shadows of the background and the color of the foreground is mixed with the color of the background, Figure 3.8(h).

$$I(b, f) = \begin{cases} \text{Multiply}(b, f) & \text{if } f \leq 0.5 \\ \text{Screen}(b, f) & \text{if } f > 0.5 \end{cases}$$

However while blending functions can attenuate the intrusiveness of inserting advertising in videos. Usually brands do not want to change their logos. Therefore, if this algorithm is supposed to be used in the market, this step would not be implemented.

3.8 Experimental Results

In order to better evaluate our algorithm, we have also implemented Tao Mei's [MHYL07] for comparison sake.

3.8.1 Hardware and Software

The algorithm was implemented using $C++$ programming language, the $g++4.8.1$ compiler and the OpenCV library for image processing and analysis. The corresponding program was run on an Intel Core 2 Quad Q9550 with 2.83Ghz processor, with 4Gb of RAM and with Linux Ubuntu 12.04 as operating system.

3.8.2 Parameters Setup

The results that will be presented bellow are relative to the implementation of our algorithm with the following parameters:

- **Video resolution.** It was chosen a default video resolution of 640x480.
- **Ad logo resolution.** The resolution for the brand logo was of 64x48 which corresponds to 10% of video resolution.
- **Preprocessing stage setup.** The Gaussian blur had a standard derivation of $\sigma = 1.4$ and a 3x3 neighbourhood.
- **Quadtree rules setup.** The minimum region size for quadtree subdivision was of 96x72 (15% fo video resolution).
- **Minimum ad time display.** In order to insert an ad in a video, it was established a minimum displaying time of 5 seconds.
- **Maximum ad time display.** It was not established a maximum displaying time for ads.
- **Timeline setup.** Only one ad can be displayed at any time, with no limit to the number of ads.

3.8.3 Visual Results

Some results can be visualized in Figure 3.9. Here we present four sets of images, where left column shows the result of the application of the uniform region detection plus the quadtree region partitioning to a video frame, while the right column consists in the insertion of the advertisement in an appropriate region of the frame. The videos were obtained from the public user uploaded videos of Youtube:

- The first row concerns a football of video a match between *Real Madrid and Barcelona*[Rea11].

- The second row concerns the videoclip associated with the sung *Get Lucky* [Pun13].
- The third row has to do with a video from BBC News [New12].
- The fourth was taken from the videoclip *Gangnam Style* [Psy13].

These four videos were chosen because of their differences in terms of category, motion and scene complexity. For example, the football video consists of the highlights of a game, which means that most of the video mainly consists on goal shots, with fast camera movements and small spaces between objects. The *Daft Punk* video frame is a good example of the lighting effects in the image, while the videoclip *Gangnam Style* is actually a very hard video for advertising insertion since the scenes are short in duration and very complex.

3.8.4 Comparison

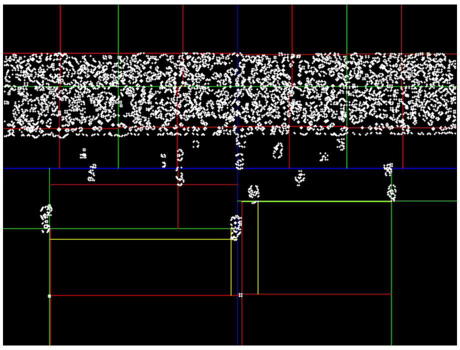
Of course the shown video frames do not fully demonstrate the capabilities of the proposed algorithm. In order to demonstrate that it was also implemented VideoSense algorithm proposed by Tao Mei's for comparison sake [MHYL07]. Since our algorithm only address the region detection for ad insertion in video, we also only implemented the ad insertion part of Tao Mei's algorithm. In order to make both algorithms in equal grounds a minimum of five second ad display and no intrusiveness was also established to VideoSense.

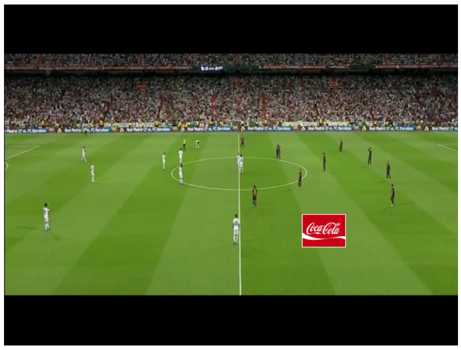
The results for a set of online videos are shown in Table 3.1. These videos are from the categories of music and entertainment, being videos with over 1 million views. The first five videos [Rea11, Sai11, Foo12, Fed12, Ten12] are videos of sports category and can be considered to have low to medium complexity. In fact, videos such as [Fed12, Ten12] represent tennis videos and like most, they have an stationary camera, having for most time only both players in movement. The following five videos are categorized as music clips ([Psy13, Thi13, Gag13, Pun13, Per12]), which have a higher complexity than the first five, e.g., [Psy13, Gag13] are videos with higher complexity due to fast camera movements and variety of scene objects. The final videos are trailers of movies [Hob13, Sil13a, End13, God13, Div13], which also belong entertainment category. These are videos with a higher complexity than the others, due to the movements in the scene and also to the higher number of visual effects [End13, God13], like flashes and explosions.

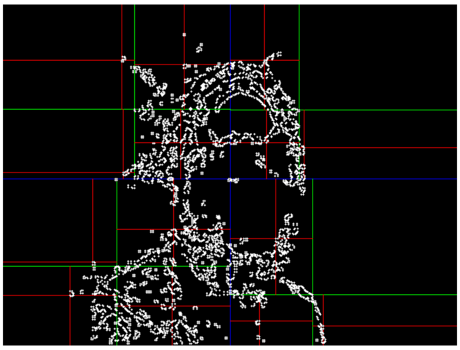
The first three columns (attributes) of the table are relative to video information. The first attribute is the *Video source* with the reference to the original video. *Video type* describes the category of the video (a sports highlight, a trailer or a music clip). Finally, the third attribute refers to the duration of the video in seconds (*Video duration*).

The *Algorithm* attribute (fourth column) is a reference to both algorithms, Tao Mei's algorithm called *VideoSense*, and our algorithm labelled *Entropy*.

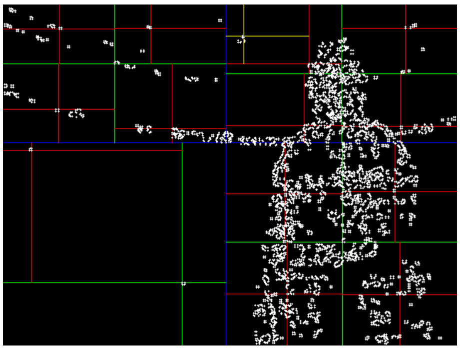
The following four attributes are the ones where the comparison between both algorithms is done. The *Ad time* attribute of Table 3.1 makes reference to the total period of time (in seconds), that an advertisement is displayed in the respective video. The difference between both algorithms, in terms of this attribute is also illustrated in Figure 3.10, where we can see


(a)

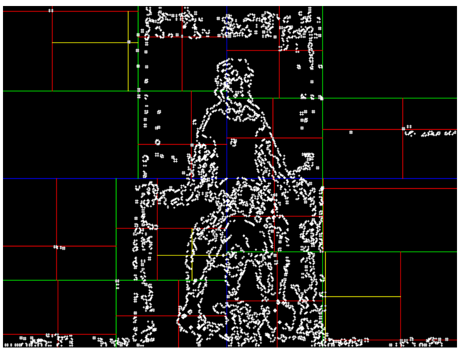

(b)


(c)


(d)


(e)


(f)


(g)


(h)

Figure 3.9: Results of the algorithm. First collumn is the uniform region detection results plus quadtree region partition, followed by the last collumn, the advertisement insertion

Table 3.1: Advertising insertion on videos, results table

Video source	Video type	Video duration (sec)	Algorithm	Ad time (sec)	Longest period (sec)	Number of ads	Mean time (sec)
Real Madrid x Barcelona[Rea11]	Football Highlights	192	Entropy	119	26.4	9	13.23
			VideoSense	72.64	13.28	9	8.04
Brazil x Honduras[Foo12]	Football Highlights	226	Entropy	106	21	15	7.1
			VideoSense	41.2	7.3	7	5.9
Magic Carpe Ride[Sai11]	Sail Highlights	290	Entropy	210	52.3	8	21
			VideoSense	48.28	10.3	6	8
Tennis Funny moments[Ten12]	Tennis Highlights	377	Entropy	165	15	24	6.9
			VideoSense	100.87	20.67	9	11.2
Roger Federer[Fed12]	Tennis Highlights	275	Entropy	153	28.7	13	11.8
			VideoSense	152	44	10	15.2
PSY - Gangnam Style[Psy13]	Music Clip	252	Entropy	51.46	12.4	8	6.43
			VideoSense	15	8.42	2	7.67
Robin Thickie Blurred Lines[Thi13]	Music Clip	271	Entropy	173	19.56	23	7.55
			VideoSense	23.23	6.13	4	5.78
Lady Gaga Bad Romance[Gag13]	Music Clip	307	Entropy	176	19.2	28	6.3
			VideoSense	7.17	7.17	1	7.17
Beyonce XO[Bey14]	Music Clip	239	Entropy	176	53.76	14	12.56
			VideoSense	60.4	13.32	8	7.52
Katy Perry Horse[Per12]	Music Clip	224	Entropy	62.1	12.6	12	5.6
			VideoSense	31.78	7.67	5	5.4
Godzilla [God13]	Video Trailer	133	Entropy	106.6	26.4	9	10,4
			VideoSense	18.14	18.14	1	18.14
Desolation of Smaug[Hob13]	Video Trailer	180	Entropy	61	10.6	19	5.7
			VideoSense	18.9	8.2	3	6.3
Divergent [Div13]	Video Trailer	150	Entropy	71.6	16.8	12	5.97
			VideoSense	5.4	5.4	1	5.4
Enders Game[End13]	Video Trailer	118	Entropy	57	13.5	9	6.3
			VideoSense	0	0	0	0
Silver Lining[Sil13a]	Video Trailer	157	Entropy	31	8.7	5	5.58
			VideoSense	5.08	5.08	1	5.08

that our algorithm is able of displaying advertisements for a longer period of time, mainly in the most complex videos, though not in a continuous manner.

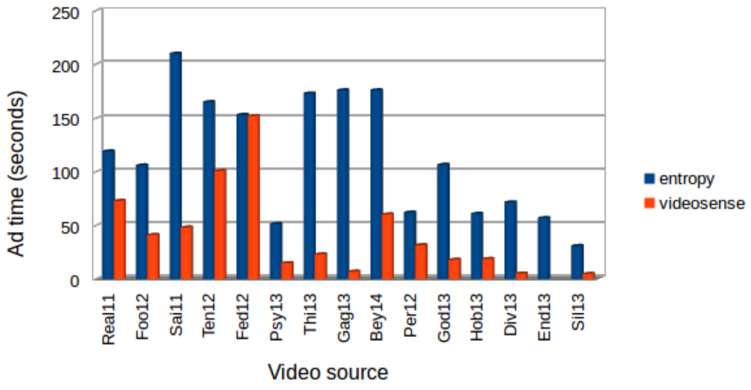


Figure 3.10: Total time in seconds that ads can be inserted in the video.

In respect to the *Longest period* of time that an ad can be displayed. Figure 3.11 shows that in general, our algorithm is capable of using continuous, longest period of time for advertising.

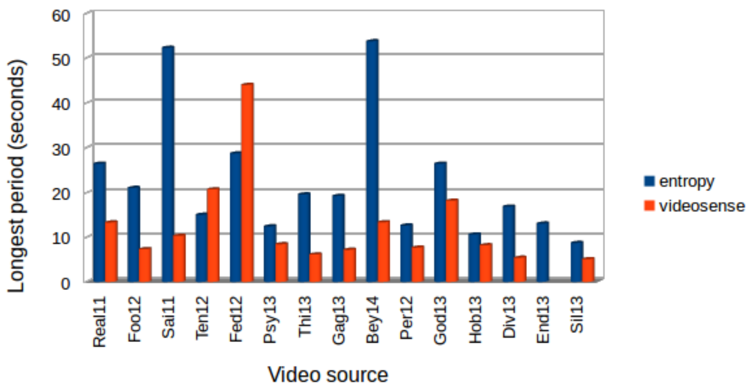


Figure 3.11: Longest period of time in seconds that one ad can be inserted in the video.

The attribute *Number of Ads* represents the quantity of ads that can be displayed during the video exhibition. Recall that in parameter setup we only allow one ad at time. As was expected from the results obtained in the last attributes, the number of ads that can be displayed in our algorithm is also higher than videosense, as illustrated in Figure 3.12

The attribute *Mean time* expressed in seconds, represents the mean time that each ad is displayed in video. In other words the, the mean time is given by the ratio of *Ad time* to the *Number of Ads*. The mean time taken by both algorithm for each video is exhibit in Figure 3.13. In spite of both algorithms can present similar mean times for displaying ads, videosense detects a number of advertising regions that is far less than those detected by our algorithm (cf. Figure 3.12) this is particularly evident for complex videos like those last four videos, namely: [Hob13, Div13, End13, Sil13a].

Note that the results shown in Figures 3.10 to 3.13 are obtained with the conditions imposed above (5 seconds minimum, no intrusiveness). Other conditions mean other results. Neverthe-

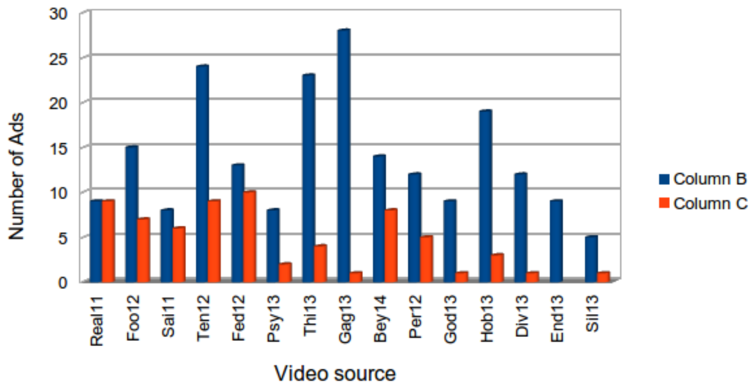


Figure 3.12: Number of ads that can be inserted in the video.

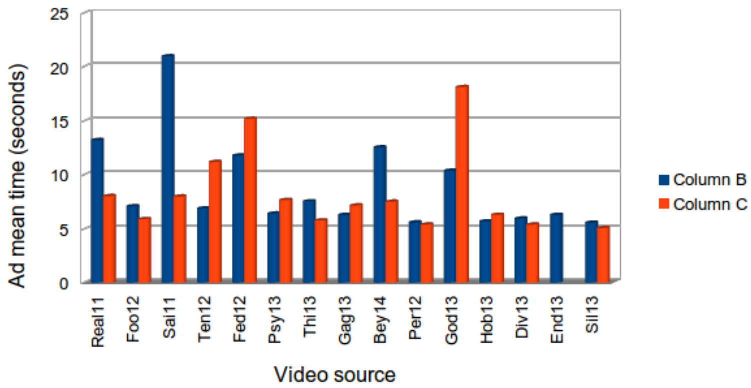


Figure 3.13: Mean time that each ad can be inserted in the video.

less, it can be said that the total duration of the advertisement is longer for both algorithms when there is not that much motion in the video as happens in the cases of [Rea11], [Sai11], [Fed12] for example.

The proposed algorithm has better results b than VideoSense especially for more complex videos. Videos such as [Psy13], [End13], [Hob13] are complex due to the constant motion and changes of color and lighting of the objects of the scene, what makes it very difficult to have long periods of time that obeys to the parameters that were defined previously, most found places for ad insertion are shorter than the five second condition that was established. That's why in videos such as [Fed12], a tennis video with a stationary camera, VideoSense can achieve very similar results to our algorithm, in terms of longest continuous period it could in fact achieve better results.

3.8.5 Speed Performance

Evaluated the performance of the proposed algorithm in terms of region detection for ad placement, is now time to also evaluate it in respect to speed. It is clear that the proposed algorithm was not designed for real-time. Even so, there is still the concern about the time that is needed to process the entire video, as well as about the best regions for ad placement.

In general terms a 4 minute video with 6000 frames at 25 frames per second, with resolution 640x480 would take approximately 40 minutes to be completely processed.

After testing our algorithm for a number of videos, we came to the conclusion that the uniform region detection stage of the algorithm was the one that had more influence on the speed performance of the corresponding program. In fact, this stage takes around 80% of the time needed to process the entire video. It was then necessary to find a way of to speed up this stage.

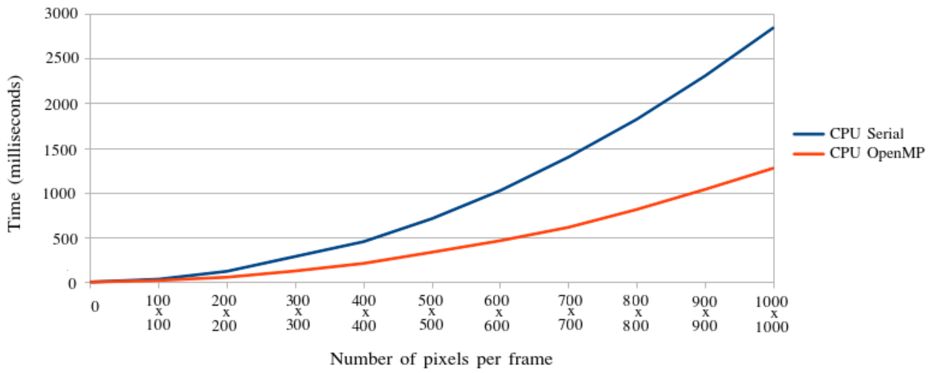


Figure 3.14: Speed performance of uniform region detection process.

After re-examining the steps of the uniform region detection stage, it was possible to determine that the problem lies in the entropy calculation of hue and saturation components. In fact, because there is not any OpenCV function to compute the entropy of an image, it was necessary to transfer the data of each video frame to a $C++$ matrix, calculating then the entropy, and transfer the entropy matrix back into an OpenCV matrix. Recall that entropy is calculated for each pixel with reference to its neighbourhood. Consequently, the bigger the video frame, the more would take for the entropy stage to finish.

As shown in Figure 3.14, for a serial CPU implementation of entropy step of our algorithm, a 1000x1000 image takes about three seconds to be processed and less than a second with half the size of the video frame. It was then clear that there was the need to reduce the image resolution as much as possible, in order to speed up the performance of the algorithm. But, this solution leads to loss of information, principally if low resolution videos are already being used.

In practice, we noted that we must use resolutions of 500x500 or higher in order to guarantee that there is not significant loss of information; hence the standard size of 640x480 resolution that we use as a minimum. This is seemingly enough to process each frame under a second and without meaningful loss of data.

As an alternative to improve of the speed performance of the algorithm, we used OpenMP to take advantage of parallel processing based on multi-core CPU multi-threading. Thus, multi-threading of the entropy step was applied, resulting in the improvement that can be observed in Figure 3.14. This way, the time needed to analyse the whole video would drop to half the time taken by serial CPU implementation. This means that a 4 minute video would take now around 18-19 minutes.

As expected, the time taken by the multithreading implementation is far better than the serial implementation, but it can be further improved. In fact, from frame to frame, the difference in motion for most videos is very small, which means that the number of frames that are needed to analyse the video can be dropped. After some testing, it was established that skipping 2 frames after every meaningful frame was feasible without loss of quality in the final result. This means that we only need to analyze $\frac{1}{3}$ of the video. Consequently, the final time needed to process and analyse the whole video would be around 6-8 minutes depending on the number of frames and the frame per second ratio.

Chapter 4

Conclusions

This dissertation describes the implementation of a novel algorithm for in-video advertising, more precisely for non-intrusive ad placement in short videos. This algorithm is specially adequate for videos with low resolutions and very short duration (around 5 minutes). It is also agnostic in terms of video genre.

4.1 Comparative Remarks

An efficient algorithm for in-video advertising is hard to conceive. In fact, it is very difficult to detect good regions for placement of ads, mainly, if the objective is to create a method capable of being used in many different videos, that is, without knowing anything about their content, or equivalently, a set of features that could be tracked in every single video. Thus, the found solution mainly consists of detecting all uniform regions in video, calculating then the best positions for the insertion of advertisements.

As shown in the previous chapter, the proposed algorithm is capable of achieving in general good results, even for complex videos. In fact, it is capable of determine the best places for ads, as well as a timeline for their insertion, without directly interfere with the scene objects of the video. As also shown above, when compared to one of the best methods for in-video advertising, Tao Mei's VideoSense, in terms of the detection of places for advertising in videos, the proposed algorithm achieves better results than Tao Mei's. Of course, we are not using, advertising contextualization as Tao Mei's and colleagues do, after all these areas are not addressed in this dissertation.

4.2 Limitations and Future Work

This dissertation introduces a new algorithm that allows the detection of specific advertisable regions in video. Nevertheless, this implementation has room for improvement. Further work will focus on two major issues: real-time and contextualization. More specifically we intend to:

1. Study and test other image processing techniques. As it could be seen in the previous section, even though pre-processing techniques are applied in the algorithm to the video, it remains some artefacts when performing the uniform region detection, which will decrease the quality of the algorithm.

2. Design and implement a parallel algorithm based on GPU, in CUDA or OpenCL, in order to improve the speed performance of the algorithm. For that reason, the principal focus in

the future, will be to come to an implementation that will perform in real-time.

3. Address the contextualization issue. The idea is to present more relevant ads to the user without compromising his/her privacy.In fact, contextualization is one of the most important factors to take into account when doing online advertising. Studies indicate that advertising has better results when the advertisement is directed to user's interests.

4. Study and implement ad insertion techniques that further reduce the intrusiveness from the user point of view.

Bibliography

[ABK+09] Florian Alt, Moritz Balz, Stefanie Kristes, Alireza Sahami Shirazi, Julian Mennenöh, Albrecht Schmidt, Hendrik Schröder, and Michael Goedicke. Adaptive user profiles in pervasive advertising environments. In *Ambient Intelligence*, volume 5859 of *Lecture Notes in Computer Science*, pages 276--286. Springer-Verlag Berlin Heidelberg, 2009. 27

[AEK00] Asim Ansari, Skander Essegaier, and Rajeev Kohli. Internet recommendation systems. *Journal of Marketing Research*, 37(3):363--375, 2000. 23

[AGM02] Micah Adler, Phillip B. Gibbons, and Yossi Matias. Scheduling space-sharing for internet advertising. *Journal of Scheduling*, 5(2):103--119, 2002. 20, 28

[Bay98] Chip. Bayers. The promise of one to one (a love story). *Wired*, 6(5):1--10, 1998. 9

[Bey14] Beyonce. Xo, brit awards 2014, 2014. Available from: `https://www.youtube.com/watch?v=2iYcC0ImdOM`. 50

[BL00] Tim Berners-Lee. *Weaving the Web: The Original Design and Ultimate Destiny of the World Wide Web*. HarperCollins Publishers, Inc., New York, NY, USA, 2000. 8

[BL04] Pierre-Jean Benghozi and Christian Licoppe. Technological national learning: From minitel to internet. In Bruce Kogut, editor, *The Global Internet Economy*, pages 153--190. The MIT Press, 2004. 7

[BM03] G Bilchev and D Marston. Personalised advertising, exploiting the distributed user profile. *BT Technology Journal*, 21(1):84--90, 2003. 27

[BS02] Patrick Barwise and Colin Strong. Permission-based mobile advertising. *Journal of Interactive Marketing*, 16(1):14--24, 2002. 18

[Cai05] Yuanzhe Cai. Electronic gaming in the digital home. Industrial Report, Volume 1, September. Parks Associates, September 2005. 24

[Cam13] Michael Campbell. *Ultimate Heat Map: How to Increase Your Advertising Revenues without Additional Traffic*. Dynamic Media Series. Dynamic Media Corporation, 2013. xvii, 12

[CBJ94] William L Cats-Baril and Tawfik Jelassi. The french videotex system minitel: A successful implementation of a national information technology infrastructure. *MIS Quarterly*, 18(1):1--20, 1994. 7

[CC06] Mark Claypool and Kajal Claypool. Latency and player actions in online games. *Communications of the ACM*, 49(11):40--45, 2006. 24

[CDL08] Xu Cheng, Cameron Dale, and Jiangchuan Liu. Statistics and social network of youtube videos. In *Quality of Service, 2008. IWQoS 2008. 16th International Workshop on*, pages 229--238. IEEE, 2008. 31

[CGJ78] Edward G Coffman, Jr, Michael R Garey, and David S Johnson. An application of bin-packing to multiprocessor scheduling. *SIAM Journal on Computing*, 7(1):1--17, 1978. 21

[Cha95] Meenakshi R Chauhan. *Advertising: The Social Ad. Challenge*. Anmol Publications, 1995. 1

[Cha08] Patrali Chatterjee. Are unclicked ads wasted ? enduring effects of banner and pop-up ad exposures on brand memory and attitudes. *Journal of Electronic Commerce Research*, 9(1):51--61, 2008. 16

[CHCW08] Chia-Hu Chang, Kuei-Yi Hsieh, Ming-Che Chung, and Ja-Ling Wu. Visa: virtual spotlighted advertising. In *Proceedings of the 16th ACM International Conference on Multimedia (MM'08)*, pages 837--840, Vancouver, Canada, October 26-31, 2008. ACM Press. 25, 28, 44

[CHCW10] Chia-Hu Chang, Kuei-Yi Hsieh, Ming-Che Chiang, and Ja-Ling Wu. Virtual spotlighted advertising for tennis videos. *Journal of Visual Communication and Image Representation*, 21(7):595--612, 2010. 25

[CHL06] Kuan-Ta Chen, Polly Huang, and Chin-Laung Lei. How sensitive are online gamers to network quality? *Communications of the ACM*, 49(11):34--38, 2006. 24

[Cis13] Cisco. Visual network index: Forecast and methodology, 2012-2017. 2013. 1

[CLL+11] Y. K. Chee, J.W.Y. Lim, K. W. Lau, I. K T Tan, and Poo Kuan Hoong. A scalable approach to real-time multiplayer online in-game advertisement via peer-to-peer. In *Proceedings of the IEEE 3rd International Conference on Communication Software and Networks (ICCSN'11)*, pages 242--246, Xi'an, China, May 27-29, May 2011. IEEE Press. 24, 28

[COSG+06] Daniel Cohen-Or, Olga Sorkine, Ran Gal, Tommer Leyvand, and Ying-Qing Xu. Color harmonization. *ACM Transactions on Graphics*, 25(3):624--630, 2006. 25, 44

[CSX07] Wen Chen, Yun Q Shi, and Guorong Xuan. Identifying computer graphics using hsv color model and statistical moments of characteristic functions. In *Multimedia and Expo, 2007 IEEE International Conference on*, pages 1123--1126. IEEE, 2007. 36

[DA12] Jason Deane and Anurag Agarwal. Scheduling online advertisements to maximize revenue under variable display frequency. *Omega*, 40(5):562--570, 2012. 21, 28

[dCS06] J.E. de Castro and H. Shimakawa. Mobile advertisement system utilizing user contextual information. In *Proceedings of the 7th International Conference on Mobile Data Management (MDM'06)*, pages 91--91, Nara, Japan, May 10-12, May 2006. IEEE Press. 22

[DeG97] Yvonne DeGraw. *User's Guide to AOLpress 2.0*. America Online, Inc, 1997. xvii, 7

[Div13] Divergent official trailer, 2013. Available from: `Availableathttp://www.youtube.com/watch?v=sutgWjz10sM`. 48, 50, 51

[DKK+00] Milind Dawande, Jayant Kalagnanam, Pinar Keskinocak, F Sibel Salman, and R Ravi. Approximation algorithms for the multiple knapsack problem with assignment restrictions. *Journal of combinatorial optimization*, 4(2):171--186, 2000. 20

[DKS03] Milind Dawande, Subodha Kumar, and Chelliah Sriskandarajah. Performance bounds of algorithms for scheduling advertisements on a web page. *Journal of Scheduling*, 6(4):373--394, 2003. 20, 28

[DKS05] Milind Dawande, Subodha Kumar, and Chelliah Sriskandarajah. Scheduling web advertisements: a note on the minspace problem. *Journal of Scheduling*, 8(1):97--106, 2005. 20, 28

[Eld11] Eric Eldon. ComScoreÕs 2011 Social Report: Facebook Leading, Microblogging Growing, World Connecting. `http://techcrunch.com/2011/12/21/comscoresocial2011`. Last visited on May 10, 2014. comScore, Inc., `http://techcrunch.com/2011/12/21/comscoresocial2011/` 2011. 23

[End13] Enders game, official trailer, 2013. Available from: `http://www.youtube.com/watch?v=vP0cUBi4hwE`. 48, 50, 51, 52

[ERK10] Michael D. Ekstrand, John T. Riedl, and Joseph A. Konstan. Collaborative filtering recommender systems. *Foundations and Trends in Human Computer Interaction*, 4(2):81--173, 2010. 23

[Fed12] Roger Federer. Top 10 insane slices, 2012. Available from: `http://www.youtube.com/watch?v=zG4iNFxScak`. 48, 50, 52

[FN04] Ari Freund and Joseph Seffi Naor. Approximating the advertisement placement problem. *Journal of Scheduling*, 7(5):365--374, 2004. 20, 28

[Foo12] Football game: Brazil x honduras., 2012. Available from: `http://www.youtube.com/watch?v=7F-7M61ecy0`. 48, 50

[FP06] Daniel C Fain and Jan O Pedersen. Sponsored search: A brief history. *Bulletin of the American Society for Information Science and Technology*, 32(2):12--13, 2006. 13

[Gag13] Lady Gaga. Bad romance, 2013. Available from: `http://www.youtube.com/watch?v=qrO4YZeyl0I`. 48, 50

[Gay07] Jonathon Gay. *The History of Flash. Adobe Systems Inc.* Adobe Systems, 2007. 17

[GJ08] J.Z. Gao and A. Ji. Smartmobile-ad: An intelligent mobile advertising system. In *Proceedings of the 3rd International Conference on Grid and Pervasive Computing Workshops (GPC Workshops'08)*, pages 164--171, Kunming, China, May 25-28, May 25-28 2008. IEEE Press. 23

[God13] Godzilla official trailer., 2013. Available from: `http://www.youtube.com/watch?v=mBwsUD7jYCI`. 48, 50

[Goo13] Google. Youtube statistics 2013, 2013. 2

[Gop10] KC Gopakumar. Advertising in kerala its influence on select consumer non durables. 2010. 1

[GT11] Avi Goldfarb and Catherine E. Tucker. Online advertising, behavioral targeting, and privacy. *Communications of the ACM*, 54(5):25--27, 2011. 24

[Ha08] Louisa Ha. Online advertising research in advertising journals: A review. *Journal of Current Issues & Research in Advertising*, 30(1):31--48, 2008. 1

[Her94] Douglas A. Hergert. *How to Use Prodigy*. How It Works (Ziff-Davis/Que). Ziff-Davis Press, 1994. 7

[HFT08] Azni H Halim, Ahmad H Fauzi, and Selviawati Tarmizi. Bluetooth mobile advertising system using pull-based approach. In *Information Technology, 2008. ITSim 2008. International Symposium on*, volume 4, pages 1--4. IEEE, 2008. 22

[HHB10] Hamed Haddadi, Pan Hui, and Ian Brown. Mobiad: private and scalable mobile advertising. In *Proceedings of the 5th ACM International Workshop on Mobility in the Evolving Internet Architecture (MobiArch'10)*, pages 33--38, New York, NY, USA, 2010. ACM Press. 22, 28

[HIH14] Michael Hitt, R. Duane Ireland, and Robert Hoskisson. *Strategic Management: Concepts and Cases: Competitiveness and Globalization*. Cengage Learning, 2014. 11

[HJ12] Charles W. L. Hill and Gareth R. Jones. *Strategic Management: An Integrated Approach*. Cengage Learning, 2012. 13

[HK01] Jonathan L Herlocker and Joseph A Konstan. Content-independent task-focused recommendation. *IEEE Internet Computing*, 5(6):40--47, 2001. 23, 28

[HK02] Shuk Ying Ho and Sai Ho Kwok. The attraction of personalized service for users in mobile commerce: an empirical study. *ACM SIGecom Exchanges*, 3(4):10--18, 2002. 22

[HML08] Xian-Sheng Hua, Tao Mei, and Shipeng Li. When multimedia advertising meets the new internet era. In *Proceedings of the 10th IEEE Workshop on Multimedia Signal Processing*, pages 1--5, Cairns, Queensland, Australia, October 8-10, October 8-10 2008. IEEE Press. 28

[Hob13] The Hobbit. The desolation of smaug, 2013. Available from: `http://www.youtube.com/watch?v=lfflhfn1W-o`. 48, 50, 51, 52

[HS02] Allan Hanbury and Jean Serra. A 3d-polar coordinate colour representation suitable for image analysis. *Computer Vision and Image Understanding*, 2002. 35

[IHKM12] Noor A Ibraheem, Mokhtar M Hasan, Rafiqul Z Khan, and Pramod K Mishra. Understanding color models: A review. *ARPN Journal of Science and Technology*, 2:265--275, 2012. 34

[JBR11] Amruta Joshi, Abraham Bagherjeiran, and Adwait Ratnaparkhi. User demographic and behavioral targeting for content match advertising. In *Proceedings of the 5th International Workshop on Data Mining and Audience Intelligence for Advertising (ADKDD'11)*, pages 53--60, San Diego, CA, USA, August 21, 2011. ACM. 27

[JLX+09] Wei Jiang, Dechao Liu, Xing Xie, Matthew R Scott, Jonathan Tien, and Dong Xiang. An online advertisement platform based on image content bidding. In *Proceedings of the 2009 IEEE International Conference on Multimedia and Expo (ICME'09)*, pages 1234--1237, New York, NY, USA, 2009. IEEE Press. 21, 22, 28

[JZFF11] Dietmar Jannach, Markus Zanker, Alexander Felfernig, and Gerhard Friedrich. *Recommender Systems: An Introduction*. Cambridge University Press, 2011. 23

[Kav98] Michael Kavanagh. New media. *Marketing Week*, 21(38):35--35, 1998. 11

[Kel96] KJ Kelly. Millard heading for internet. *Advertising Age*, 67(34):32, 1996. 11

[KJS06] Subodha Kumar, Varghese S Jacob, and Chelliah Sriskandarajah. Scheduling advertisements on a web page to maximize revenue. *European Journal of Operational Research*, 173(3):1067--1089, 2006. 21, 28

[KLPC09] YoungSuk Kim, JoonWoo Lee, SeongRae Park, and ByoungCheol Choi. Mobile advertisement system using data push scheduling based on user preference. In *Proceedings of the 2009 Wireless Telecommunications Symposium (WTS'09)*, pages 1--5, Prague, Czech Republic, April 22-24, April 22-24 2009. IEEE Press. 23, 28

[KLW+07] Sheng-Po Kuo, Shih-Ching Lin, Bing-Jhen Wu, Yu-Chee Tseng, and Chung-Chou Shen. Geoads: A middleware architecture for music service with location-aware advertisement. In *Proceedings of the IEEE International Conference on Mobile Adhoc and Sensor Systems (MASS'07)*, pages 1--3, Pisa, Italy, October 8-11, 2007. IEEE Press. 23

[Kri01] David M Kristol. Http cookies: Standards, privacy, and politics. *ACM Transactions on Internet Technology*, 1(2):151--198, 2001. 9

[KS05] Jay P Kesan and Rajiv C Shah. Shaping code. *Harvard Journal of Law & Technology*, 18(2):320 -- 399, 2005. 9, 11

[Lam04] Chuck Lam. Snack: incorporating social network information in automated collaborative filtering. In *Proceedings of the 5th ACM Conference on Electronic Commerce (EC'04)*, pages 254--255, New York, NY, USA, May 17-20, 2004. ACM Press. 23, 28

[LAR00] Weiyang Lin, Sergio A Alvarez, and Carolina Ruiz. Collaborative recommendation via adaptive association rule mining. In *Proceedings of the International Workshop on Web Mining for E-Commerce (WebKDD'00)*, Boston, MA, USA, August 20, 2000. 23, 28

[LCH08] Wei-Shing Liao, Kuan-Ting Chen, and Winston H Hsu. Adimage: video advertising by image matching and ad scheduling optimization. In *Proceedings of the 31st Annual International ACM Conference on Research and Development in Information Retrieval (SIGIR'08)*, pages 767--768, Singapore, Singapore, July 20-24, 2008. ACM Press. 26, 28

[LEL02] Hairong Li, Steven M Edwards, and Joo-Hyun Lee. Measuring the intrusiveness of advertisements: Scale development and validation. *Journal of advertising*, 31(2):37--47, 2002. 32

[LJHX08] Huiying Liu, Shuqiang Jiang, Qingming Huang, and Changsheng Xu. A generic virtual content insertion system based on visual attention analysis. In *Proceedings of the 16th ACM International Conference on Multimedia (MM'08)*, pages 379--388, Vancouver, British Columbia, Canada, October 27-31, 2008. ACM Press. 25, 28

[LNA+99] Marc Langheinrich, Atsuyoshi Nakamura, Naoki Abe, Tomonari Kamba, and Yoshiyuki Koseki. Unintrusive customization techniques for web advertising. *Computer Networks*, 31(11):1259--1272, 1999. 24

[LNOS99] Suzanne L LeMole, Steven Howard Nurenberg, Joseph Thomas O'neil, and Peter H Stuntebeck. Method and system for presenting customized advertising to a user on the world wide web, 1999. US Patent 6,009,410. 23

[LR97] Enno Littmann and Helge Ritter. Adaptive color segmentation-a comparison of neural and statistical methods. *Neural Networks, IEEE Transactions on*, 8(1):175--185, 1997. 34

[LS02] S. Y. Lee and S. S. Sundar. Psychological effects of frequency and clutter in web advertising. In *Proceedings of the 52th Annual Conference of the International Communication Association (ICA'02)*, Seoul, South Korea, July 15-19, 2002. 19

[LVY08] Dimitris Liapis, Spyridon Vassilaras, and Gregory S Yovanof. Implementing a low-cost, personalized and location based service for delivering advertisements to mobile users. In *3rd International Symposium on Wireless Pervasive Computing (ISWPC'08)*, pages 133--137, Santorini, Greece, May 7-9, 2008. IEEE Press. 23

[LWYX05] Yiqun Li, Kong Wah Wan, Xin Yan, and Changsheng Xu. Real time advertisement insertion in baseball video based on advertisement effect. In *Proceedings of the 13th Annual ACM International Conference on Multimedia (MM'05)*, pages 343--346, Hilton Hotel, Singapore, November 6-12, 2005. ACM Press. 25, 28

[LZL12] Yongkun Li, Bridge Qiao Zhao, and John Lui. On modeling product advertisement in large-scale online social networks. *IEEE/ACM Transactions on Networking*, 20(5):1412--1425, 2012. 13, 14

[MA04] Syam Menon and Ali Amiri. Scheduling banner advertisements on the web. *INFORMS Journal on Computing*, 16(1):95--105, 2004. 20, 28

[Man04] Andrea Mangani. Online advertising: Pay-per-view versus pay-per-click. *Journal of Revenue and Pricing Management*, 2(4):295--302, 2004. 20

[MDLN02] Bamshad Mobasher, Honghua Dai, Tao Luo, and Miki Nakagawa. Discovery and evaluation of aggregate usage profiles for web personalization. *Data Mining and Knowledge Discovery*, 6(1):61--82, 2002. 24, 28

[Meh12] Aranyak Mehta. Online matching and ad allocation. *Theoretical Computer Science*, 8(4):265--368, 2012. 22

[MGA94] Ken McCarthy, Mark Graham, and Marc Andreessen. Panel discussion on multimedia publishing on the internet, 1994. The 1st Internet Marketing Conference, Pacific Bell's Yerba Buena Media Center, San Francisco, USA, November 5. 10

[MGHL10] Tao Mei, Jinlian Guo, Xian-Sheng Hua, and Falin Liu. Adon: toward contextual overlay in-video advertising. *Multimedia Systems*, 16(4-5):335--344, 2010. 26, 28

[MHL08] Tao Mei, Xian-Sheng Hua, and Shipeng Li. Contextual in-image advertising. In *Proceedings of the 16th ACM International Conference on Multimedia (MM'08)*, pages 439--448, Vancouver, British Columbia, Canada, October 27-31, 2008. ACM Press. 26

[MHYL07] Tao Mei, Xian-Sheng Hua, Linjun Yang, and Shipeng Li. VideoSense: towards effective online video advertising. In *Proceedings of the 15th International Conference on Multimedia (MM'07)*, pages 1075--1084, Augsburg, Germany, 2007. ACM Press. 26, 31, 47, 48

[Miy08] Anthony D. Miyazaki. Online privacy and the disclosure of cookie use: Effects on consumer trust and anticipated patronage. *Journal of Public Policy & Marketing*, 27(1):19--33, 2008. 9

[MM07] Boris Mordkovich and Eugene Mordkovich. *Pay-per-click Search Engine Marketing Handbook: Low Cost Strategies to Attracting New Customers Using Google, Yahoo & Other Search Engines*. MordComm, Inc., USA, 2007. 13

[MNS07] Mohammad Mahdian, Hamid Nazerzadeh, and Amin Saberi. Allocating online advertisement space with unreliable estimates. In *Proceedings of the 8th ACM Conference on Electronic Commerce (EC'07)*, pages 288--294, San Diego, California, USA, 2007. ACM Press. 21

[Mof12] John Moffat. Cookie Law Ð what is to be done? IP Europe Quarterly, 2012. Avidity IP Ltd. Available from: `http://www.avidity-ip.com/assets/pdf/cookielawsep12.pdf`. 10

[Mos95] Mosaic. NCSA Mosaic for the X Window System User Guide, Version 2.6 1. National Center for Supercomputing Applications, University of Illinois at Urbana-Champaign, USA, September 1995. xvii, 10

[MR00] Raymond J Mooney and Loriene Roy. Content-based book recommending using learning for text categorization. In *Proceedings of the Fifth ACM Conference on Digital Libraries (DL'00)*, pages 195--204, San Antonio, Texas, USA, 2000. ACM Press. 23

[MRT14] Perry Marshall, Mike Rhodes, and Bryan Todd. *Ultimate Guide to Google AdWords: How to Access 1 Billion People in 10 Minutes*. Ultimate Series. Entrepreneur Press, 2014. 12, 13

[MSVV07] Aranyak Mehta, Amin Saberi, Umesh Vazirani, and Vijay Vazirani. Adwords and generalized online matching. *Journal of the ACM*, 54(5):22, 2007. 21, 28

[NA05] Atsuyoshi Nakamura and Naoki Abe. Improvements to the linear programming based scheduling of web advertisements. *Electronic Commerce Research*, 5(1):75--98, 2005. 24

[Nak02] Atsuyoshi Nakamura. Improvements in practical aspects of optimally scheduling web advertising. In *Proceedings of the 11th International Conference on World Wide Web*, pages 536--541, Honolulu, Hawaii, USA, 2002. ACM Press. 24

[New01] D Newman. Impersonal interaction and ethics on the world-wide-web. *Ethics and Information Technology*, 3(4):239 -- 246, 2001. 16

[New12] BBC News. What is freedom, 2012. Available from: `http://www.youtube.com/watch?v=T0ifg5wj39I`. 48

[Nic94] Leslie H Nicoll. An introduction to the Internet part I: history, structure, and access. *Journal of Nursing Administration*, 24(3):9--11, 1994. 5

[NKY04] M.R. Nelson, H. Keum, and R.A. Yaros. Advertainment or adcreep game players attitudes toward advertising and product placements in computer games. *Journal of Interactive Advertising*, 5(1):3--21, 2004. 24

[Ots75] Nobuyuki Otsu. A threshold selection method from gray-level histograms. *Automatica*, 11:285--296, 1975. 38, 39

[Pal05] Daniel E Palmer. Pop-ups, cookies, and spam: toward a deeper analysis of the ethical significance of internet marketing practices. *Journal of Business Ethics*, 58(1-3):271--280, 2005. 16

[Paz99] Michael J Pazzani. A framework for collaborative, content-based and demographic filtering. *Artificial Intelligence Review*, 13(5-6):393--408, 1999. 23

[PCG03] Danny Poo, Brian Chng, and Jie-Mein Goh. A hybrid approach for user profiling. In *Proceedings of the 36th Annual Hawaii International Conference on System Sciences (HICSS'03)*, pages 103.2,1--9, Hilton Waikoloa Village, Big Island, Hawaii, USA, January 6-9, 2003. IEEE Computer Society. 27

[Per12] Katy Perry. Dark horse ft. juicy j, 2012. Available from: `http://www.youtube.com/watch?v=0KSOMA3QBU0`. 48, 50

[pho00] Adobe photoshop 6.0 users guide. *Adobe Systems Inc.*, pages 109--114, 2000. 44

[PMB96] Michael Pazzani, Jack Muramatsu, and Daniel Billsus. Syskill & webert: Identifying interesting web sites. In *Proceedings of 13th National Conference on Artificial*

Intelligence, pages 54--61, Portland, Oregon, USA, August 4Ð8, 1996. AAAI Press. 27

[Por11] The Statistics Portal. Global video games advertising revenue from 2007 to 2016 (in billion u.s. dollars). The Statistics Portal,http://www.statista.com/statistics/238140/global-video-games-advertising-revenue, last visited on May 10, 2014, 2011. 24

[PP93] AR Plastino and A Plastino. Stellar polytropes and tsallis' entropy. *Physics Letters A*, 174(5):384--386, 1993. 38

[Pre00] Frank Presbrey. *The History and Development of Advertising*, volume 1. 2000. 1

[Psy13] Psy. Gangnam style, 2013. Available from: http://www.youtube.com/watch?v=9bZkp7q19f0. 48, 50, 52

[Pun13] Daft Punk. Get lucky, 2013. Available from: http://www.youtube.com/watch?v=h5EofwRzit0. 48

[QK96] JA Quelch and LR Klein. The internet and international marketing. *Sloan Management Review*, 37(3):60--75, 1996. 14

[Ram12] John Rampton. Why Google Beat Inktomi: the Inside Story From Former Engineer. Search Engine Watch, May 2012. 13

[RB98] Nathan Rae and Mike Brennan. The relative effectiveness of sound and animation in web banner advertisements. *Marketing Bulletin*, 9:76--82, 1998. 12

[RCE05] Omer Rashid, Paul Coulton, and Reuben Edwards. Implementing location based information/advertising for existing mobile phone users in indoor/urban environments. In *Proceedings of the International Conference on Mobile Business (ICMB'05)*, pages 377--383, Sydney, Australia, July 11-13, 2005. IEEE Press. 23

[Rea11] Real madrid vs fc barcelona, match highlights, 2011. Available from: http://www.youtube.com/watch?v=9F1rC8Xa34Z. 47, 48, 50, 52

[Rei97] Robert H. Reid. *Architects of the Web: 1,000 Days that Built the Future of Business*. John Wiley & Sons, Inc., 1997. xvii, 11

[RMJF09] M.A. Rosso, M.K. McClelland, B.J. Jansen, and S.W. Fleming. Using Google AdWords in the MBA MIS Course. *Journal of Information Systems Education*, 20(1):41--50, 2009. 13

[Sai11] Sail - magic carpet ride., 2011. Available from: http://www.youtube.com/watch?v=1SN1gSkqvy0. 48, 50, 52

[Sam06] Hanan Samet. *Foundations of multidimensional and metric data structures*. Morgan Kaufmann, 2006. 39

[Sch01] John Schwartz. Giving the web a memory cost its users privacy. *New York Times*, 4(01), 2001. 9

[SF87] C.H. Sandage and Varnon Fryburge. *TAdvertising Theory and Practice*. 1987. 1

[Sha01] Claude Elwood Shannon. A mathematical theory of communication. *ACM SIGMOBILE Mobile Computing and Communications Review*, 5(1):3--55, 2001. 37

[Sil13a] Silver linings playbook official trailer, 2013. Available from: `http://www.youtube.com/watch?v=Lj5_FhLaaQQ`. 48, 50, 51

[Sil13b] David Silverman. IAB internet advertising revenue report 2013: first six months' results. PricewaterhouseCoopers LLP, New York, NY, USA, October 2013. 1, 24

[SNC13] Ana Stanescu, Swapnil Nagar, and Doina Caragea. A hybrid recommender system: User profiling from keywords and ratings. In *Proceedings of the 2013 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology*, volume 1, pages 73--80, Atlanta, GA, USA, November 17-20, 2013. IEEE Press. 23

[SQP02] Shamik Sural, Gang Qian, and Sakti Pramanik. Segmentation and histogram generation using the hsv color space for image retrieval. In *Image Processing. 2002. Proceedings. 2002 International Conference on*, volume 2, pages II--589. IEEE, 2002. 35

[SSQN09] Ross Shannon, Matthew Stabeler, Aaron Quigley, and Paddy Nixon. Profiling and targeting opportunities in pervasive advertising. In *Proceedings of the 1st Workshop on Pervasive Advertising*, held in conjunction with the *7th International Conference on Pervasive Computing*, Nara, Japan, May 11-14, 2009. 26

[ST12] ValŐrie Schafer and Benjamin G. Thierry. *Le Minitel, l'enfance numŐrique de la France*. Nuvis, Paris, France, 2012. 7

[Swi98] Kara Swisher. *aol.com: How Steve Case Beat Bill Gates, Nailed the Netheads, and Made Millions in the War for the Web*. Random House Inc., New York, NY, USA, 1998. 6

[Tay13] Gabriela Taylor. *Advertising in a Digital Age: Best Practices for AdWords and Social Media Advertising*. Give Your Marketing a Digital Edge Series. Global & Digital, 2013. 19

[TBP09] Michael Trusov, Randolph E Bucklin, and Koen Pauwels. Effects of word-of-mouth versus traditional marketing: findings from an internet social networking site. *Journal of marketing*, 73(5):90--102, 2009.

[Ten12] Top 15 funny and amusing tennis moments, 2012. Available from: `https://www.youtube.com/watch?v=QV5dYTl4c0w`. 48, 50

[Thi13] Robin Thicke. Blurred lines ft. t.i., pharrell, 2013. Available from: `http://www.youtube.com/watch?v=yyDUC1LUXSU`. 48, 50

[TNB+10] Vincent Toubiana, Arvind Narayanan, Dan Boneh, Helen Nissenbaum, and Solon

Barocas. Adnostic: Privacy preserving targeted advertising. In *Proceedings of the 17th Network and Distributed System Security Symposium (NDSS'10)*, The Dana on Mission Bay, San Diego, California, USA, February 28 - March 3, February 28 - March 3 2010. Internet Society, Reston, VA, USA. 27

[Tom00] John A Tomlin. An entropy approach to unintrusive targeted advertising on the web. *Computer Networks*, 33(1):767--774, 2000. 24

[TS12] Bo Tan and R Srikant. Online advertisement, optimization and stochastic networks. *IEEE Transactions on Automatic Control*, 57(11):2854--2868, 2012. 21, 28

[TYZZ10] Jie Tang, Limin Yao, Duo Zhang, and Jing Zhang. A combination approach to web user profiling. *ACM Transactions on Knowledge Discovery from Data*, 5(1):2:1--2:44, 2010. 26

[Vai11] Siva Vaidhyanathan. *The Googlization of Everything*. University of California Press, 2011. 11

[Vie91] John L. Viescas. *The Official Guide to the Prodigy Service*. Microsoft Press, 1991. xvii, 8

[VM05] David A. Vise and Mark Malseed. *The Google Story*. Delacorte Press and Random House, Inc., 2005. 13

[Wag93] Richard J. Wagner. *Inside Compuserve*. New Riders Publishers, 1993. xvii, 6

[Web13] Marc Weber. Endangered online worlds. `http://www.computerhistory.org/atchm/endangered-online-worlds`, 2013. Last visited May 10, 2014. xvii, 9

[Wol94] Gary Wolfe. The (second phase of the) revolution has begun. *Wired*, 2(10):1--11, 1994. 8

[XLL08] David Jingjun Xu, Stephen Shaoyi Liao, and Qiudan Li. Combining empirical experimentation and modeling techniques: A design research approach for personalized mobile advertising applications. *Decision Support Systems*, 44(3):710--724, 2008. 23

[XWBT05] Changsheng Xu, Kong Wah Wan, Son Hai Bui, and Qi Tian. Implanting virtual advertisement into broadcast soccer video. In *Proceedings of the 5th Pacific Rim Conference on Advances in Multimedia Information Processing (PCM'04)*, volume 3332 of *Lecture Notes in Computer Science*, pages 264--271, Tokyo, Japan, November 30 - December 3, November 30 - December 3 2005. Springer-Verlag. 19, 25, 28

[YDCL06] Wan-Shiou Yang, Jia-Ben Dia, Hung-Chi Cheng, and Hsing-Tzu Lin. Mining social networks for targeted advertising. In *Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06)*, pages 137.1--137.11, Hyatt Regency Kauai, Hawai, USA, January 4-7, January 4-7 2006. IEEE Computer Society. 24, 28

[YKS04] Chan Yun Yoo, Kihan Kim, and Patricia A Stout. Assessing the effects of animation in online banner advertising: Hierarchy of effects model. *Journal of Interactive Advertising*, 4(2):49--60, 2004. 17

[YQ] Weilong Yang and Zhensong Qian. Understanding the characteristics of category-specific youtube videos. 31

[YT03] Soe-Tsyr Yuan and You Wen Tsao. A recommendation mechanism for contextualized mobile advertising. *Expert Systems with Applications*, 24(4):399--414, 2003. 22, 28