

Sharing Video Emotional Information in the Web

Eva Oliveira, Digital Games Research Centre (DIGARC), Polytechnic Institute of Cávado and Ave, Barcelos, Portugal

Teresa Chambel, LaSIGE, University of Lisbon FCUL, Lisbon, Portugal

Nuno Magalhães Ribeiro, Centro de Estudos e Recursos Multimediáticos (CEREM), Universidade Fernando Pessoa, Porto, Portugal

ABSTRACT

Video growth over the Internet changed the way users search, browse and view video content. Watching movies over the Internet is increasing and becoming a pastime. The possibility of streaming Internet content to TV, advances in video compression techniques and video streaming have turned this recent modality of watching movies easy and doable. Web portals as a worldwide mean of multimedia data access need to have their contents properly classified in order to meet users' needs and expectations. The authors propose a set of semantic descriptors based on both user physiological signals, captured while watching videos, and on video low-level features extraction. These XML based descriptors contribute to the creation of automatic affective meta-information that will not only enhance a web-based video recommendation system based in emotional information, but also enhance search and retrieval of videos affective content from both users' personal classifications and content classifications in the context of a web portal.

Keywords: Domain Specific Extensible Markup Language (XML) Schema, User Physiological Signals, Video Access, Video Affective Classification, Video Recommendation, Video Search

1. INTRODUCTION

With the advent of rich interactive multimedia content over the Internet in such environments as educational or entertainment, the way people use online multimedia content, such as film viewing, video and image sharing, asks for new ways to access, explore and interact with such information (Purcell, 2010). Video on the Web has been in explosive growth, which improves the fullness of the user experience but leads to new challenges in content discovery,

searching and accessing. Information needs to be labeled or annotated to be accessible, shared and searchable. The Multimedia Information Retrieval (MIR) research area is still trying to find solutions to automated content and users analysis techniques, and annotation techniques for media, as a result of a huge need of descriptors (metadata) of contents that can be understood by computers and accessible to humans. Also, data quality for Web portals consumers is still in debate and new methods to ensure and improve data quality are being

DOI: 10.4018/ijwp.2013070102

studied (Herrera et al., 2010). Thus, there is a need for automatic methods for gathering information both from multimedia objects (video, images, audio, text) and from users (preferences, emotions, likings, comments, descriptions, annotations), and subsequently making this information available, searchable and accessible (Lew, 2006). In the literature, there are several studies that have attempted to define standards to establish structures of descriptors and concepts for affective applications in their categorization issues (Devillers, Vidrascu & Lamel, 2005; Douglas-Cowie et al., 2007; Luneski & Bamidis, 2007; Schroder et al., 2007). One of the first works developed towards this goal was the HUMAINE database, despite the fact that it did not propose a formal definition to structure emotions, but simply identified the main concepts.

It is clear that there is a demand for new tools that enable automatic annotation and labeling of digital videos. In addition, the improvement of new techniques for gathering emotional information about videos, be it through content analysis or user implicit feedback through user physiological signals, is revealing a set of new ways for exploring emotional information in videos, films or TV series. In fact, gathering emotional information in this context brings out new perspectives to personalize user information by creating emotional profiles for both users and videos. In a collaborative web environment, the collection of users profiles and video profiles has the potential to: (a) empower the discovery of interesting emotional information in unknown or unseen movies, (b) compare reactions to the same movies among other users, (c) compare directors' intentions with the effective impact on users, and (d) analyze, over time, our own reactions or directors' tendencies. The reason for the growing interest in emotion research lies precisely in the importance of the emotions for human beings. According to Axelrod and Hone (2006), emotions are currently regarded as important for human development, in social relationships and in the context of thinking processes such as reasoning, problem solving, motivation, consciousness, memory, learning,

and creativity. Thus, the relationship between people and the world they live in is clearly emotional. Nowadays, with technological development, the world in which people live also implies computers and their applications. When considering this particular relation it becomes evident that we must support user experiences that are engaging and enjoyable.

The attempt to define a standardized description of emotions faces several challenges and some questions naturally arise. There is more than one theory of emotions and there is also no common agreement on the quantity and the actual names of emotions. Curiously, when trying to define emotion, we encountered a multitude of definitions and models in the literature. As stated by Fehr and Russell (1984) "everyone knows what an emotion is, until asked to give a definition." (p. 464). Despite this fact, we have some main theories defining emotions and how they can be understood. Throughout our review, we examine findings in three different perspectives: the categorical, the dimensional and the appraisal. The categorical or discrete model of emotions defines emotions as discrete states. These states are well-defined units that identify a certain behavior and experience. One of the major research programs on emotional expressions was developed by Paul Ekman (1992) (Figure 1). His multicultural research project tested thousands of people from all over the globe. It turns out as commonly accepted that six basic emotions (anger, fear, surprise, sadness, disgust, happiness) represent innate and universal emotions recognized in face expressions across cultures. However, surprise has been withdrawn from the basic emotions since his later article (Ekman, 1999). One of the most notorious dimensional theorists is Russel (1980), who proposed a circumplex model of emotions, in which one central dimension defines the polarity (positive/negative or pleasant/unpleasant) of the emotion and the other defines the level of activation. Russel bases his theory on a layman's conceptualization of affect and on multivariate analysis of self-reported affective states, by showing that there are two predominant dimensions that participants use

to communicate and label their own emotional experience. The appraisal theory of emotions is essentially a categorical emotional model that suggests that emotion elicitation and differentiation depend on people's own evaluation of events and its circumstances. In fact, it was Magda Arnold 1960 who first called "appraisal" for categorizing emotions based on people's own judgment and according to their experiences (Scherer, 1999). Klaus Scherer defends that emotions are triggered by people's own interpretation of events, i.e. by their subjective interpretations and considers that appraisals emerges from the following sequence: novelty, pleasantness, own goals, causes and compatibility with standards. Despite the fact that there are different theories, there is some agreement that some recognition techniques might be used, such as physiological patterns, brain and speech changes, or facial expressions.

In this chapter we review current challenges in developing web portals for digital video content dissemination and then analyze the information requirements for creating a semantic representation of such a system based on the exploration of the emotional components of movies, regarding their implicit impact on users and in the affective categorization of content by users perspective (manual input). We then propose a semantic description of emotion oriented towards the user experience when watching videos and finally, we conclude by suggesting a domain specific XML schema that will provide information in a collaborative web-based recommendation system that is based on emotional information on videos.

Figure 1. IFelt emotional vocabulary

```
<vocabulary type="category" id="iFeltEmotions">
  <item name="happy" />
  <item name="amused"/>
  <item name="involved"/>
  <item name="inspired"/>
  <item name="tender"/>
  <item name="surprised"/>
  <item name="astonished" />
  <item name="curious"/>
  <item name="melancholic"/>
  <item name="bored"/>
  <item name="compassioned"/>
  <item name="fear"/>
  <item name="disturbed" />
  <item name="amused"/>
  <item name="scared"/>
  <item name="disgust"/>
  <item name="embarrassed"/>
  <item name="anger"/>
  <item name="irritated" />
</vocabulary>
```

2. RELATED WORK

2.1. Web Portals for Digital Video

Web portals have been commonly used as websites that allow users to customize their homepage by adding widgets onto it. According to Omar (2007), such an approach provides the user with complete control over the content displayed on users' personal pages, the location for such content, and the means to interact with it. Furthermore, web portals allow users to control the multimedia data that is presented, provides a platform that enables the mash-up of technologies and data, enables different services to be consumed and enable the aggregation of relevant content from heterogeneous sources with user contributed content, as well as user feedback on the content using tagging and rating.

Web portals for digital video dissemination can be considered one of the most successful web applications of the Web 2.0 generation. In fact, web video portal sites provide users with a personal homepage with facilitates access to video information gathered from different websites. Such portals provide dashboards that enable the delivery of content aggregation both for individual users and enterprises alike. Video portals can thus be used as content repositories for various kinds of video, including generic video clips, public movie clips and trailers, documentaries and TV series excerpts. Such portals also need to provide client-side interactivity, improved usability and fast performance. Such requirements are often supported through the use of widgets which provide specific functionalities while keeping simple core architecture for the web video portal.

On the other hand, the growth in access to multimedia information and applications, made possible by the advances in Internet and World Wide Web technologies, caused new challenges for information search and retrieval (Prusky, Guelgi & Reynaud, 2011; Varela, Putnik & Ribeiro, 2012). In this context, portals need to provide such capabilities and services in order to meet requirements for consistent administration, appearance, and navigation across all sources of multimedia content. In addition, portals should

also support personalization in order to make available the required tools and information to different users (Wong & Adamson, 2010).

According to Ben Natan et al. (2004), Web portals became the standard for delivering Web applications as portal plugins or portlets, independently of whether the domain is consumer or business applications. Portals have therefore become the accepted user interface for Web applications. For example, major consumer websites, such as Amazon, Yahoo or YouTube, commonly present a portal look and feel. Web portals are successful essentially because they aggregate important functions such as: integration, presentation, organization, and personalization, in highly complex application environments which tend to provide a large number of different applications and support large user populations.

In particular, Web video portals offer huge and diverse collections of audiovisual data to the public, including public media archives of large national broadcasters (Schneider et al., 2012). Indeed, in recent years, the growth in multimedia storage and the declining costs for storing multimedia data gave rise to increasingly larger numbers of digital videos available online in video repositories, making it increasingly difficult to retrieve the relevant videos from such large video repositories according to users' interests (Calic et al., 2005). The same difficulties in finding efficient methods for indexing multimedia have been felt in the context of lecture video portals (Haojin et al., 2011), making efficient search and retrieval of videos still a challenging task. Therefore, there is a strong need to make the unstructured digital video data accessible and searchable with great ease and flexibility, in particular in the context of web video portals.

2.2. Extracting and Analyzing Emotional Data

Since William James (1984), it is known that corporal changes are correlated with emotions, which turned possible the modulation of emotions through the evaluation of physiological patterns (Rainville, Bechara, Naqvi & Damásio,

2006) which, in turn, unveiled the possibility of the automatic recognition of emotions from such patterns.

The Autonomic Nervous System (ANS) is part of the peripheral nervous system that has the function of conducting and regulating corporal processes such as sensory impulses from the blood, heart, respiration, salivation, perspiration or digestion. This system is divided into two parts: the parasympathetic nervous system (PSNS) responsible to calm our system down, and the sympathetic nervous system (SNS) that has the function to prepare our body to stress conditions. For example, meditation is characterized by the activation of the PSNS, while in running situations the SNS is activated using body energy (blood pressure increases, heart beats faster, digestion slows down) to react accordingly.

Some authors claim that there are distinctive patterns of ANS for anger, fear, disgust, sadness or happiness (Ekman, Levenson & Friesen, 1983b). These evidences led to many advances in the study of emotion, and the most common ways to measuring it include the following: self-reports, autonomic measures (physiological measures), startle responses magnitudes (verbal reaction of sudden stimuli), brain states and behavior (vocal, facial, body postures)

Biosensors or physiological sensors are used to gather these body changes. In fact, it was precisely through the analysis of the variations of the ANS that Damásio (1995) tested the somatic markers hypothesis which states that, before we rationalize any decision, our body reduces our options by corporal and somatic changes based in our past experiences. Thus, from this study, we conclude that emotions can be characterized by somatic patterns and that every somatic pattern could be evaluated by the analysis of ANS components variation (Mauss, 2009).

From Ekman's work, it was also evident that an emotion-specific autonomic pattern could be distinguishable besides its valence and arousal, because emotions of the same valence appear very distinguishable when analyzing hear-rate,

skin temperature, skin resistance and forearm flexor muscle. Several other studies show a direct correlation between emotion categories and physiological pattern. For example heart rate has been used to differentiate positive from negative emotions, suggesting that several emotions can be predicted and defined by the analysis of patterns of cardio (heart-rate) and respiratory activity (Friedman & Thayer, 1998; Rao & Vikram, 2001).

Besides these evidences, the characterization of emotions by physiological patterns faces some problems, despite its advantages when compared to other recognition methods. The main limitation is the difficulty in discriminating emotions from physiological signals. Other problem lies in finding the adequate elicitation technique to target a specific emotion (Rainville, Bechara, Naqvi & Damásio, 2006). Emotions are time, space, context and individual based, so trying to find a general pattern for emotions can be difficult. Moreover, it is also difficult to obtain a "ground truth". These are some of the major problems, when compared to facial and vocal recognition. Although emotions can be characterized by some physiological variations, machine-learning techniques may be applied in automatic emotion recognition methods, based on pattern recognition, to deal with huge amount of data needed to be analyzed.

The collection of physiological data produced while users are watching movies was recently developed in psychology to test whether films can be efficient emotional inductors, which could help psychologists in specific treatments (Kreibig, Wilhelm, Roth & Gross, 2007), or in the computer science area to automatically summarize videos according to the emotional impact on viewers (Soleymani, Chanel, Kierkels & Pun, 2009).

The major advantage is that the characterization of emotions from physiological patterns cannot be intentional, as people cannot trigger the autonomic nervous system (ANS) contrarily to the so called "poker face" where people disguise expressions as well as vocal utterances.

Another common argument against physiological measurements for emotion analysis is

the fact that sensors might be invasive. However, nowadays, sensors are less intrusive (e.g. wearable, made of rubber) and they allow protecting peoples' identity or appearance, which could be an advantage when compared with techniques like, for example, facial recognition.

Physiological data allows for the development of systems that facilitate the understanding of cognitive, emotional and motivational processes, by giving access to emotional information that can inform about the type of engagement of a user when interacting with a computer, for example, when performing a task or watching a video.

Although emotions can be characterized by some physiological variations, machine-learning techniques may be applied in automatic emotion recognition methods, based on pattern recognition, to deal with huge amount of data needed to be analyzed. The following section discusses how recent studies are processing physiological data to recognize emotions.

2.3. Semantically Representing Emotions

2.3.1 EARL

One of the first works (Schroder, Pirker & Lamolle, 2006) towards the standardization of the representation of emotions was the Emotion Annotation and Representation Language (EARL), which aims to represent emotions suitable for the most common use cases: 1) manual annotation of emotional content, 2) affect recognition systems, and 3) affective

generation such as that performed by speech synthesizers. Because there is no agreed upon model of emotions, and there is more than one way to represent an emotion (e.g. dimensional, categorical), EARL leaves freedom for users to manage their preferred emotion representation, by creating XML schemas for domain-specific coding schemas embedded in EARL, that serves application cases which demand for specific data categorization (Schroder et al., 2006). This constitutes one of the advantages of EARL, and the other is the fact that being an XML-based language, it standardizes the representation of data, allowing for re-use and data-exchange with other technological components (Schroder et al., 2007).

In order to provide suitable descriptions among the different use-cases, EARL assumes descriptions for the following information presented in Table 1. Schroder et al. (2007) argue that these are the informative topics needed to describe simple use-cases that use only emotional labels to process their information.

An EARL example of a description that needs to use a simple emotion to represent a text that aims to sound pleasurable, could be written in the following simple structure

```
<emotion category="pleasure">Nice to meet you!</emotion>
```

Complex emotions, as considered in the context of EARL, are composed of several elements, such as more than one emotion and the probability of each one occurring. In the

Table 1. EARL emotional description minimal requirements

Emotional Data	Description
Emotion descriptor	Any emotional representation set
Intensity	Intensity of an emotion expressed in numeric, discrete values
Regulation types	Which encode a person's attempt to regulate the expression of her emotions
Scope of an emotion label	Link to an external media object, text, or other modality
Combination	Co-occurrence of emotions and their dominance
Probability	Labeler's degree of confidence

following example presented in Box 1, we have a description of an image with two emotional categories and their intensities.

An example of video annotation with a simple emotion could be as follows:

```
<emotion category="pleasure" probability="0.4" start="0.5" end="1.02"
xlink:href="video.avi"/>
```

While a video annotation with a complex emotion could be represented as follows in Box 2.

Other example, that is important to the context of this work, is the representation of emotions recognized from sensors while users watch a video clip, such as the following in Box 3.

EARL is constructed with modules, which allow for the development of new dialects by combining a base XML schema with other

XML schema “plugins”. Three examples of plugins are the emotional definitions, such as the categorical, the dimensional and the appraisal, so any application can use these EARL dialects according to their needs, but can also develop different EARL documents with new specifications. In fact, EARL can also be used integrated with other languages like the Extensible Multimodal Annotation markup language (EMMA, 2010), used to represent information automatically extracted from a variety of inputs such as speech, natural language text and ink input, providing a set of elements and attributes focused on enabling annotations on user inputs and interpretations of these inputs.

The integration of EARL with EMMA can be useful to add an emotion component on EMMA’s user input interpretations and can be made via EMMA’s extensible content representation mechanism. For example, an interpretation of emotion on an EMMA element

Box 1.

```
<complex-emotion xlink:href="face12.jpg">
  <emotion category="pleasure" probability="0.5"/>
  <emotion category="friendliness" probability="0.5"/>
</complex-emotion>
```

Box 2.

```
<complex-emotion start="0.5" end="1.02" xlink:href="video.avi">
  <emotion category="pleasure" intensity="0.7"/>
  <emotion category="worry" intensity="0.5"/>
</complex-emotion>
```

Box 3.

```
<complex-emotion xmlns="http://emotion-research.net/earl/040/posneuneg"
xlink:href="clip123.avi">
  <complex-emotion modality="biosignal" start="0.387" end="0.416">
    <emotion category="positive" probability="0.1"/>
  <complex-emotion modality="biosignal" start="0.417" end="0.597">
    <emotion category="neutral" probability="0.4"/>
  <complex-emotion modality="biosignal" start="0.598" end="0.897">
    <emotion category="negative" probability="0.05"/>
  </complex-emotion>
</complex-emotion>
```

using EARL complex emotion representation could be represented as follows in Box 4.

EARL was the first movement towards the creation of a standard semantic representation of emotion.

2.3.2. EmotionML

The second step resulted in the Emotion Markup Language. The Emotion Markup Language (Emotion ML) was born to define a general-purpose emotion annotation and representation language. After the definition of EARL, the respective working group (Schröder et al., 2011) moved to the World Wide Web Consortium (W3C) in the form of two incubator groups. First, an Emotion Incubator group was set to analyze use cases and requirements of a markup language, and then the Emotion Markup Language Incubator group to dissect the requirements of such a language. Like EARL, the first W3C incubator group defined a standard for representing and processing emotions related information in technological environments.

The work group opted to use XML as the semantic representation language because its standardization allows the easy integration and communication with external applications by having a standard emotional representation structure that enables other technological artifacts and applications to understand and process data. In fact, the most recent markup language is defined in XML, which appears to be a good choice. Emotion ML is presently in the Second Public Working Draft (W3C working draft) after

the First Public Working Draft (FPWD), which was published in 2009. The FPWD proposed elements of a syntax to address use-cases in what regards emotion annotation, the automatic recognition of user-related emotions and the generation of emotion-related system behavior.

As EARL, Emotion ML does not enclose annotated emotions, but uses XML attributes to represent the type of data to be presented. For example, there is an attribute – “expressed-through” – that is used when considering annotation or recognition use-cases to specify where the emotion is expressed, whether by face, voice, posture or physiological data.

As an example of the application of this attribute, we might use it in a video annotation in Emotion ML such as the following Box 5.

An example of the representation of the automatic recognition of emotions using physiological sensors could be written as follows in Box 6.

As can be seen in the semantic representations above, the development of technological support by using XML structures for human activities that are based on emotional aspects requires the representation of different components. The Emotion Markup Language notably considered a proper body of use cases to set a general structure that supports and enables the communication between technological components regarding the emotional properties of, among others, images, videos, text, automatic recognition of emotions, emotion synthesis and speech. For example, SMIL (Bulterman, Dick & Rutledge, Lloyd, 2008) is a presentation-level

Box 4.

```
<emma:emma version="1.0" xmlns:emma="http://www.w3.org/2003/04/emma"
  xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
  xmlns:earl="http://emotion-research.net/earl/040/posneuneg">
  <emma:interpretation id="int1">
    <earl:complex-emotion>
      <earl:complex-emotion modality="biosignal">
        <earl:emotion category="positive" probability="0.1"/>
        <earl:emotion category="neutral" probability="0.4"/>
        <earl:emotion category="negative" probability="0.05"/>
      </earl:complex-emotion>
    </earl:complex-emotion>
  </emma:interpretation>
</emma:emma>
```


Box 5.

```

<emotionml xmlns=http://www.w3.org/2009/10/emotionml"
xmlns:meta="http://www.example.com/metadata"
category-set=http://www.example.com/custom/emotv-labels.xml expressed-
through="biosignal">
<emotion>
  <category name="irritation" value="0.46"/>
  <reference uri="file:ext03.avi?t=3.24,15.4"/>
</emotion>
<emotion>
  <category name="despair" value="0.48"/>
  <reference uri="file:ext03.avi?t=5.15,17.9"/>
</emotion>
</emotionml>

```

XML language that combines animation and media objects into a single presentation in an interactive way. It controls the temporal and spatial characteristics of media and animations elements in an interactive interface. Emotion ML can be used as a specialized plug-in language for SMIL as an emotion engine to thrill facial and vocal expressions.

2.3.4. Other Semantic Representations

De Carolis et al. (2001) present an Affective Presentation Markup Language (APML) which is also an XML based language used to represent face expressions of their agents dialogs, in their work on Embodied Animated Agents (ECA). Other research work related with emotion concepts representation is ALMA (Gebhard, 2005), a layered model of affect, also called AffectML, whose main purpose is to represent affect and moods in their virtual humans'

project. The interesting aspect of this project is that, in a first phase, they use emotions as a medium-term-affect representation, and later, as a long-term representation of the personality of their characters. Both APLM and AffectML were developed within affective applications to endure the affective needs.

3. A STUDY ON ANNOTATING EMOTIONS FROM USERS WHEN WATCHING MOVIES

There is a difficulty on what regards the selection of an appropriate annotation scheme, together with a proper set of semantic labels, to structure and identify emotions (Devillers, Vidrascu, & Lamel, 2005), because different application contexts demand for specific labels for emotional data annotation. As stated before, some works already focused this issue along with other issues such as the development

Box 6.

```

<emotionml xmlns=http://www.w3.org/2009/10/emotionml
category-set="http://www.w3.org/TR/emotion-voc/xml#everyday-categories">
...
<emotion start="1006526160" end="1268647330"
  expressed-through="physiology">
  <category name="excited"/>
  <reference uri="http://www.example.com/physiodb#t=19,101"/>
</emotion>
<emotion start="2346526520" end="5438647330" expressed-through="physiology">
  <category name="angry"/>
  <reference uri="http://www.example.com/physiodb2#t=2,6"/>
</emotion>
</emotionml>

```

of semantic representations and descriptions of emotions in different contexts (Devillers, Vidrascu & Lamel, 2005; Douglas-Cowie et al., 2007).

In this section we first propose a set of annotation requirements for emotion-oriented video applications in order to define the specific labels needs in this context and then we proceed by presenting a first semantic representation proposal based in XML, a standard language that can be used in multiple technological environments.

We started this task by carrying out the requirements analysis of our specific video applications and found some guidelines that we believe are important and should therefore be followed. In this section we present such a set of classification considerations for emotion annotation related with video affective properties in order to help creating a mechanism for obtaining meaningful affective information from the perspective of viewers affective impact. Subsequently, we present an XML schema consisting of a set of semantic descriptors based on both user physiological signals, captured while watching videos (to properly characterize our classification method) and also based on video low-level features extraction.

3.1. Classification Requirements

We now discuss a set of classification considerations related with the representation of video affective properties in order to help creating a mechanism for obtaining meaningful affective information from the perspective of viewers and movies affective impact. Addressing the problem of the different annotation requirements, we established the most relevant aspects that must be included in a classification procedure, in order to enable the creation of emotion-oriented applications that include video, users and their affective relationship.

One of the first aspects to consider is the choice of a standard semantic representation for emotional information: in fact we believe that such a representation must possess the following characteristics (Oliveira, Ribeiro, & Chambel, 2010):

- It must be simple enough so that emotions can be captured from the diversity of existing emotional data gathering methods;
- It should be readable by any module of an emotion processing system;
- It should be structured in accordance with the W3C Emotion Markup Language guidelines (Schroder, Wilson, Jarrold & Evans, 2008) so as to enable the communication among future web services.

The second aspect to take into consideration is the importance of the movie collection, that should cover each and every basic high intensity emotion in order to ensure that we have, at least, one recognized emotional category. Additionally, a neutral state must also be included in the list of basic emotions, which corresponds to the occurrence of an emotionless moment in the video.

The third aspect concerns the information requirements of such a classification system. In fact, the classification of a user's subjective emotions, acquired both from physiological signal analysis and from user's manual classifications implies having classified at least the following information:

- The user's affective perspective for every video from emotional impact perspectives.
- The basic emotion for each scene in the video, in order to have a complete affective description of the whole video along its complete duration.
- An emotional profile constituted by all user's subjective emotional (user's emotional impact) classification based on physiological data and manual input of every movie.
- A video emotional profile constituted by all users' classifications.
- User emotional profiles are constructed over time by collecting and analyzing all emotional user data detected for each video scene.

The three major emotional models presented in the introduction should be represented,

if possible, in every classification of every scene, improving the access and interaction with emotional data.

As described above, we have a considerable amount of emotional data to process, which demands for suitable structures that allow the annotation of this information in videos and users' profiles. In the following section we describe the information requirements for such a classification system.

3.2. Information Requirements

The exploration and access of movies by their emotional dimensions involves a great amount of information. Here, we first present the information that needs to be structured in order to be accessible in an emotional perspective by users' point of view, videos and their relationships, and then we propose a semantic description of emotion oriented towards the user experience while watching videos, considering the user implicit assessment (by acquiring physiological signals) and the user explicit assessment (manual classification). In this way, we gather information about users, videos and their relationships (user-video): Table 2, Table 3 and Table 4 detail such information.

In each table, we represent the subjective emotional information and we explicitly indicate the way used to obtain such information – either through the classification of the physiological signals or through the manual input from users. Some studies use movies' emotional information to automatically summarize videos according to the emotional impact (Soleymani, Chanel, Kierkels & Pun, 2009), or to detect video emotional highlightings from physiological signals (Smeaton and Rothwell, 2009). This novel compilation of information

presented in Tables 2, 3 and 4 is focused on classification and annotation to explore and share movie impact on users. Thus, we structured it, in a XML file, by defining a schema and using the Emotion ML specification in order to turn this information organized and sharable. Such a structure is presented in the following section.

It is important to note that there is also non-emotional information that we suggest should be included as meta-information about videos. The other types of information that we believe are also needed can be gathered through a standard API from online services like IMDb. More specifically, we are considering using the title of the video, a link to the IMDb description, the year of release, a URL to the cover, users' ratings registered in IMDb, the first of the directors, the genres, plot, and information on all the actors (or the number selected) listed in the main title page (name, link to actor page, link to picture and character). Also interesting is to include the movie reviews from the New York ¹ critics that can be gathered to complete the movie profile general information.

After determining the information requirements we will present our system, iFelt and then propose a data structure to organize emotional information about users when watching movies.

4. IFELT SYSTEM

iFelt is an interactive web video application that allows to catalog, access, explore and visualize emotional information about movies. It is being designed to explore the affective dimensions of movies in terms of their properties and in accordance with users' emotional profiles, choices and states, in two main components. The Emotional Movie Content Classification

Table 2. Emotional information: User

Subjective Emotions (User Felt Emotion)	Physiologic Sensors	Most felt category /valence
		Less felt category /valence
		Most recent category/valence

Table 3. Emotional information: Video

Subjective Emotions (User Felt Emotion)	Physiologic Sensors	All users dominant emotions (Mean SD)
		All users most felt emotions per scene (Mean SD)
		All users dominant emotions along a movie (Mean SD)
		All users valences per movies and scenes (Mean SD)
		All users intensities per movies and scenes (Mean SD)
	User self-Assessment	All users self assessment about felt dominant emotion (Mean SD)
		All users self assessment about felt intensity of dominant emotion (Mean SD)
		All users self assessment about Felt valence (Mean SD)
		All users preferences about the movie (0-9) (Mean SD)

aims to provide video classification and indexing based on emotions, either expressed in the movies (objective emotions), or felt by the users (subjective emotions), as dominant emotions at the level of the movie or the movie scenes. Objective emotions are being classified with the aid of video low-level feature analysis, combined with audio and subtitles processing in VIRUS research project (Langlois et al., 2010); while subjective emotions can be classified manually, or automatically recognized with biometric methods based on physiological signals, such as respiration, heart rate and galvanic skin response, employing digital signal processing and pattern recognition algorithms, inspired by statistical techniques used by (Picard, 2001).

This process and its results are thoroughly described in (Oliveira et al., 2011).

4.1. Emotional ML structure for iFelt

We followed the Emotion ML recommendation for the classification of iFelt movies, their users and the relationships users/movies. Emotional ML, being an XML based language, standardizes the representation of emotional data, allowing the re-use and data-exchange with other technological components, following the guidelines we suggested above for emotional semantic representations. This information is linked as metadata to every video in our system

Table 4. Emotional information: User-video relationship

Subjective Emotions (User Felt Emotion)	Physiologic Sensors	Most felt category /valence
		Less felt category /valence
		Category felt each 5 seconds
		Global percentage of categorical/valence
		Main variances between emotional states (in every movie and all over the time)
	User self-assessment	Dominant felt emotion all over the movie
		Intensity of the felt dominant emotion
		Valence felt
		Intensity of the valence felt
		Preference about the movie (0-9)

but it was still not used or even tested for the purposes of this work.

In order to have our emotional labels well specified we created a vocabulary, as Emotion ML guidelines suggest. For that reason, inside the main vocabulary file of Emotional ML we inserted our set of emotions, like the ones in Figure 1. The vocabulary element has two main attributes: a) type, to specify the type of emotions between the traditional emotional models and b) id, to identify the list of emotions to be used in external files.

We have created three Emotion ML files and an XML schema to ensure that our data structure can be divided into a user emotional profile, a movie emotional profile and a user-movie classification. This division further enables the reuse of the information of just the user, just the movie emotional information, or just the relationship among both of them, or even the three simultaneously.

The XML schema we created has, as its main objective, to structure the information about users, movies and user-movies relationships. It also includes additional information that our system requires, such as last emotions, lists of users, lists of movies and users' preferences. As an example, the following code snippet (Figure 2) illustrates the definition of the movie information.

In this example, we have, as an XML element, the tag `MovieInformation` that includes a `movieId`, a title, a director, a country, a year and a list of actors. This tag is going to be used in the movie Emotion ML file inside the `info` tag (Figure 3), which is the way Emotion ML allows us to introduce metadata into their files. We also have a list of user is related to this specific movie, which can easily inform us about each user classification for this movie. The second part of the `movie.xml` file is concerned with the emotion classification (Figure 4).

In Figure 4, the `emotion` tag has only the global classifications of a movie including all forms of classification: manual for both iFelt emotional labels and the dimensional model measures (arousal, valence), and automatic through biosensors. The attribute `expressed-through`

allows specifying how information was gathered. We only presented an example for each case, and also for an iFelt vocabulary.

The user's information has the same structure of the movie's information (see Figure 6), being the first part about the iFelt information requirements: 1) User general information, as name, number of movies watched, number of neighbors and country; 2) Last Emotions, presents a list of movies and the associated emotion; and 3) List of Movies that this user watched.

Every file header includes the Emotion ML namespace, the reference to the vocabularies to be used, as well as the schema created (see Figure 5).

The second part (similar to Figure 4) also presents global classifications of all forms of classification but from a user perspective: manual, for both iFelt emotional labels and the dimensional model measures (arousal, valence), and automatic, through the usage of biosensors.

The second part (similar to Figure 4) also presents global classifications of all forms of classification but from a user perspective: manual, for both iFelt emotional labels and the dimensional model measures (arousal, valence), and automatic, through the usage of biosensors.

The third file, `user-movie.xml`, specifies every emotional classification (categorical or dimensional) along the movie, acquired through biosensors, and the final classification manual, which was manually inserted by the user. Thus, besides the general information about users and movies, we have the emotional classification as illustrated in Figure 7.

Thus, Figure 7 shows three types of emotional information about a user and a specific movie. The first two emotion tags specify, emotionally, a movie in 5 second range intervals by using a relative time, following Emotion ML specification. Clipping the movie by time, is denoted by the name `t`, and specified as an interval with a begin time and an end time. In this case, we have an example from the second 110 until the second 115, with an emotional classification of "happy", gathered through biosensors. Manual input can be specified using the text value for the `expressed-through`

Figure 2. *iFelt* schema: Movie information definition

```

<xsd:element name="MovieInformation" type="xsd:string"/>
  <xsd:complexType>
    <xsd:sequence>
      <xsd:element name="MovieId" type="xsd:id" use="required"/>
      <xsd:element name="Title" type="xsd:string" use="required"/>
      <xsd:element name="Director" type="xsd:string" use="required"/>
      <xsd:element name="Country" type="xsd:string" use="required"/>
      <xsd:element name="Year" type="xsd:string" use="required"/>
      <xsd:element name="Actors" maxOccurs="unbounded">
        <xsd:complexType>
          <xsd:sequence>
            <xsd:element name="name" type="xsd:string"/>
          </xsd:sequence>
        </xsd:complexType>
      </xsd:element>
    </xsd:sequence>
  </xsd:complexType>
</xsd:element>
</xsd:sequence>
</xsd:complexType>

```

attribute. In fact, this value can be used for both categorical and dimensional (valence, arousal) classifications. In this example, the dimensional classification value represents the intensity of the dimension, being 0.3 a low-than-average arousal, and a 0.9 value a very positive valence.

Having this information annotated and available, we believe it is now easier to develop an interface with other systems that may wish to use this information. Affective information of users acquired while watching videos has

specific data requirements to be represented. Having video emotionally classified will further allow for finding interesting emotional information in unknown or unseen movies, and it will also allow for the comparison among other users' reactions to the same movies, as well as comparing directors' intentions with the effective emotional impact on users, and also analyze users' reactions over time or even detect directors' tendencies. This classification can subsequently contribute to the

Figure 3. *iFelt* Emotion ML specification part 1: movie.xml

```

<info>
  <iFelt:MovieInformation>
    <iFelt:MovieID>MMMM</iFelt:MovieID>
    <iFelt:Title>Cashback</iFelt:Title>
    <iFelt:Director>Sean Ellis</iFelt:Director>
    <iFelt:Year>2009</iFelt:Year>
    <iFelt:Actors>
      <iFelt:Actor>Tom B</iFelt:Actor>
      <iFelt:Actor>Ann A</iFelt:Actor>
    </iFelt:Actors>
  </iFelt:MovieInformation>
</info>

<info>
  <iFelt:ListUsers>
    <iFelt:UserID>XXXXXX</iFelt:UserID>
    <iFelt:UserID>XXXXX0</iFelt:UserID>
    <iFelt:UserID>XXXXX1</iFelt:UserID>
    <iFelt:UserID>XXXXX2</iFelt:UserID>
    <iFelt:UserID>XXXXX3</iFelt:UserID>
    <iFelt:UserID>XXXXX4</iFelt:UserID>
  </iFelt:ListUsers>
</info>

```

Figure 4. *iFelt Emotion ML specification part 2: movie.xml*

```

<emotion expressed-through="text">
  <category name="curious" value="0.5"/>
</emotion>

<emotion expressed-through="biosignal">
  <category name="happy"/>
</emotion>

<emotion expressed-through="text">
  <dimension name="arousal" value="0.3"/>
</emotion>

<emotion expressed-through="text">
  <category name="involved" value="0.4"/>
</emotion>

<emotion expressed-through="text">
  <category name="happy" value="0.3"/>
</emotion>

<emotion expressed-through="text">
  <iFelt name="inspired" value="0.2"/>
</emotion>

<emotion expressed-through="text">
  <category name="sad" value="0.18"/>
</emotion>

<emotion expressed-through="text">
  <category name="melancholic" value="0.1"/>
</emotion>

<emotion expressed-through="text">
  <dimension name="arousal" value="0.3"/>
</emotion>

</emotionml>

```

specification of a software tool, which enables the personalization of TV guides according to individual emotional preferences and states, and recommend programs or movies based on those preferences and states.

5. CONCLUSION

In this chapter we reviewed the most relevant research works that focus in the representation of emotions, analyzing how emotional models present emotions and how actual systems that explore emotional information use such representations in their work. From the review

presented in this chapter we may conclude that there is no report in current literature concerning the representation of movies either by the emotional impact on viewers or by its content. This review also made clear that there is an effort to develop standards concerning the representation of emotions, but also that there isn't yet a closed solution for this representation. Recent studies reveal that there are specific data that needs to be assembled in order to obtain, not only quantitative but also qualitative information about users while watching videos. The aggregation of such data items will further improve a collaborative recommendation system due to

Figure 6. *iFelt Emotion ML specification part 1: user.xml*

```

<info>
  <iFelt:UserInformation>
    <iFelt:UserID>XXXXXX</iFelt:UserID>
    <iFelt:name>MaryFond</iFelt:name>
    <iFelt:NumberMovies>123</iFelt:NumberMovies>
    <iFelt:NumberNeighbors>34</iFelt:NumberNeighbors>
    <iFelt:Country>Portugal</iFelt:Country>
  </iFelt:UserInformation>
</info>

<info>
  <iFelt:LastEmotions>
    <iFelt:Position>1</iFelt:Position>
    <iFelt>Curious</iFelt:Emotion>
    <iFelt:MovieTitle>24 Hour Party People</iFelt:MovieTitle>
  </iFelt:LastEmotions>
  <iFelt:LastEmotions>
    <iFelt:Position>2</iFelt:Position>
    <iFelt:Emotion>Involved</iFelt:Emotion>
    <iFelt:MovieTitle>Black Swan</iFelt:MovieTitle>
  </iFelt:LastEmotions>
  <iFelt:LastEmotions>
    <iFelt:Position>3</iFelt:Position>
    <iFelt:Emotion>Tender</iFelt:Emotion>
    <iFelt:MovieTitle>Breakfast in Pluto</iFelt:MovieTitle>
  </iFelt:LastEmotions>
</info>

<info>
  <iFelt:ListMovies>
    <iFelt:MovieID>MMMMM</iFelt:MovieID>
    <iFelt:MovieID>XXXXX1</iFelt:MovieID>
    <iFelt:MovieID>XXXXX2</iFelt:MovieID>
    <iFelt:MovieID>XXXXX3</iFelt:MovieID>
    <iFelt:MovieID>XXXXX4</iFelt:MovieID>
  </iFelt:ListMovies>
</info>

```

Figure 5. *iFelt XML headers*

```

<?xml version="1.0" encoding="UTF-8"?>
<emotionml xmlns="http://www.w3.org/2009/10/emotionml"
  category-set="http://www.w3.org/TR/emotion-voc/xml#big6"
  appraisal-set="http://www.w3.org/TR/emotion-voc/xml#scherer-appraisals"
  dimension-set="http://www.w3.org/TR/emotion-voc/xml#scherer-dimension"
  iFelt-set="/Users/oliveira/Dropbox/_Tese/XMLImplementation/vocabulary.xml"
  xmlns:iFelt="/Users/oliveira/Dropbox/_Tese/XMLImplementation/iFelt.xsd">

```


Figure 7. *iFelt Emotion ML specification part 2: user.xml*

```

<info>
  <iFelt:MovieInformation>
    <iFelt:MovieID>MMMMM</iFelt:MovieID>
    <iFelt:name>Cashback</iFelt:name>
    <iFelt:Director>Sean Ellis</iFelt:Director>
    <iFelt:Year>2009</iFelt:Year>
    <iFelt:Actors>
      <iFelt:Actor>Tom B</iFelt:Actor>
      <iFelt:Actor>Ann A</iFelt:Actor>
    </iFelt:Actors>
  </iFelt:MovieInformation>
</info>

<emotion expressed-through="biosignal">
<reference uri="movieId.avi#t=105,110"/>
<category name="happy"/>
</emotion>

<emotion expressed-through="biosignal">
<reference uri="movieId.avi#t=115,120"/>
<category name="curious"/>
</emotion>

<emotion expressed-through="text">
<category name="happy" value="0.7"/>
</emotion>

<emotion expressed-through="text">
<category name="curious" value="0.3"/>
</emotion>

<emotion expressed-through="text">
<dimension name="arousal" value="0.3"/>
</emotion>

<emotion expressed-through="biosignal">
<dimension name="valence" value="0.9"/>
</emotion>

```

the wider range of data to relate. In one hand, physiological signals results can show significant differences between users responses to the same movie scene, other conclusions reveals that some arousal result from users, watching

the same scene are captured by different physiological signals, which shows one more time the existence of important information that collected in a user profile can enhance search and recommendation in a collaborative context.

The development of such profiles requires semantic descriptions to allow the analysis of user preferences.

We demonstrated the possibility of structuring the emotional information manipulated in our system based on a W3C standard. This fact allows us to conclude that our system might be universally understandable by other systems, given that such a system has the advantage of being opened to external communication with other systems that might require, or need, to use the emotional information acquired and stored in our system. We believe that the structure we proposed may provide emotional meaning and organization for movies, both as a collection and as media linked to a user, as well as provide machine understandable meaning to a user profile in what concerns a person's psychological profile, constructed while the person is watching a movie. The possibility of sharing such information also provides a small contribution to the information retrieval area, specifically in order to enhance search mechanisms by adding new search criteria. Given that Web portals need quality data to be returned to users, and video is an increasingly used digital media, our work could contribute to enhance web video portals to alleviate issues and difficulties related with search and retrieval of video information pertaining to users' interests and preferences.

REFERENCES

- Al Zabir, O. (2007). *Building a web 2.0 portal with Asp.Net 3.5* (1st ed.). O'Reilly.
- Ben-Natan, R., Sasson, O., & Gornitsky, R. (2004). *Mastering IBM websphere portal server: Expert guidance to build and deploy portal applications*. John Wiley & Sons.
- Bulterman, D. C. A., & Rutledge, L. (2008). *SMIL 2.0: Interactive multimedia for web and mobile devices*. Amsterdam: Springer.
- Calic, J., Campbell, N., Dasiopoulou, S., & Kompatsiaris, Y. (2005). A survey on multimodal video representation for semantic retrieval, computer as a tool. In *Proceedings of the International Conference on EUROCON 2005* (vol. 1, pp.135,138, 21-24).
- Damasio, A. (1995). *Descartes' error*. New York, NY: Harper-Collins.
- De Carolis, B., De Rosis, F., Carofiglio, V., Pelachaud, C., & Poggi, I. (2001). Interactive information presentation by an embodied animated agent. In *Proceedings of the International Workshop on Information Presentation and Natural Multimodal Dialogue* (pp. 14-15).
- Devillers, L., Vidrascu, L., & Lamel, L. (2005). Challenges in real-life emotion annotation and machine learning based detection. *Neural Networks*, 18, 407-422. doi:10.1016/j.neunet.2005.03.007 PMID:15993746
- Douglas-Cowie, E., Cowie, R., Sneddon, I., Cox, C., Lowry, O., Mcrorie, M., & Batliner, A. (2007). The HUMAINE database: Addressing the collection and annotation of naturalistic and induced emotional data. In *Proceedings of the Affective Computing and Intelligent Interaction* (pp. 488-500). Amsterdam, Netherlands: Springer
- Ekman, P. (1992). Are there basic emotions? *Psychological Review*, 99, 550-553. doi:10.1037/0033-295X.99.3.550 PMID:1344638
- Ekman, P. (1999). Basic emotions. T. Dalgleish & M. Power (Eds.), *Handbook of cognition and emotion* (pp. 45-60). Sussex, UK: Wiley.
- Ekman, P., Levenson, R. W., & Friesen, W. V. (1983). Autonomic nervous system activity distinguishes among emotions. *Science*, 221, 1208-1210. doi:10.1126/science.6612338 PMID:6612338
- EMMA. Extensible Multimodal Annotation Markup Language. (2010, May). *EMMA: Extensible multimodal annotation markup language*. Retrieved from <http://www.w3.org/TR/emml/#s3.2>
- Fehr, B., & Russell, J. (1984). Concept of emotion viewed from a prototype perspective. *Journal of Experimental Psychology*, 113, 464-486. doi:10.1037/0096-3445.113.3.464
- Friedman, B. H., & Thayer, J. F. (1998). Autonomic balance revisited: Panic anxiety and heart rate variability. *Journal of Psychosomatic Research*, 44, 133-151. doi:10.1016/S0022-3999(97)00202-X PMID:9483470

- Gebhard, P. (2005). ALMA: A layered model of affect. In *Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems* (pp. 29-36). New York, NY: ACM Digital Library.
- Haojin, Y., Siebert, M., Luhne, P., Sack, H., & Meinel, C. (2011, November 28-December 1). Lecture video indexing and analysis using video OCR technology, signal-image technology and internet-based systems (SITIS). In *Proceedings of the 2011 Seventh International Conference on* (pp.54-61).
- Herrera, M., Moraga, M. A., Caballero, I., & Coral, C. (2010). Quality in use model for web portals (QiUWeP). In F. Daniel & F. M. Facca (Eds.), *Proceedings of the 10th International Conference on Current Trends in Web Engineering (ICWE'10)* (pp. 91-101). Springer-Verlag, Berlin, Heidelberg.
- Kreibig, S. D., Wilhelm, F. H., Roth, W. T., & Gross, J. J. (2007). Cardiovascular, electrodermal, and respiratory response patterns to fear- and sadness-inducing films. *Psychophysiology*, *44*, 787–806. doi:10.1111/j.1469-8986.2007.00550.x PMID:17598878
- Lew, M., Sebe, N., Djeraba, C., & Jain, R. (2006). Content-based multimedia information retrieval: State of the art and challenges. In *Proceedings of the Transactions on Multimedia Computing, Communications, and Applications (TOMCCAP)*.
- Luneski, A., & Bamidis, P. D. (2007). Towards an emotion specification method: Representing emotional physiological signals. In *Proceedings of the Twentieth IEEE International Symposium on Computer-Based Medical Systems (CBMS'07)* (pp. 363-370).
- Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. *Cognition and Emotion*, *23*, 209–237. doi:10.1080/02699930802204677 PMID:19809584
- Oliveira, E., Benovoy, M., Ribeiro, N., & Chambel, T. (2011). Towards emotional interaction: Using movies to automatically learn users' emotional states. In *Proceedings of the Human-Computer Interaction-Interact 2011* (pp. 152-161).
- Oliveira, E., Ribeiro, N., & Chambel, T. (2010, April 10-15). Towards enhanced video access and recommendation through emotions. In *Proceedings of the "Brain, Body and Bytes: Psychophysiological User Interaction" Workshop, at ACM CHI'2010*, Atlanta, GA.
- Picard, R. W., Vyzas, E., & Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *23*(10), 1175–1191. doi:10.1109/34.954607
- Pruski, C., Guelfi, N., & Reynaud, C. (2011). Adaptive ontology-based web information retrieval: The TARGET framework. [IJWP]. *International Journal of Web Portals*, *3*(3), 41–58. doi:10.4018/IJWP.2011070104
- Purcell. (2010). *The state of online video*. Retrieved (June, 2010) from <http://www.pewinternet.org/Reports/2010/State-of-Online-Video.aspx>
- Rainville, P., Bechara, A., Naqvi, N., & Damasio, A. R. (2006a). Basic emotions are associated with distinct patterns of cardiorespiratory activity. *International Journal of Psychophysiology*, *61*, 5–18. doi:10.1016/j.ijpsycho.2005.10.024 PMID:16439033
- Rainville, P., Bechara, A., Naqvi, N., & Damasio, A. R. (2006a). Basic emotions are associated with distinct patterns of cardiorespiratory activity. *International Journal of Psychophysiology*, *61*, 5–18. doi:10.1016/j.ijpsycho.2005.10.024 PMID:16439033
- Russell, J. A. (1980). A circumplex model of emotion. *Journal of Personality and Social Psychology*, *39*, 1161–1178. doi:10.1037/h0077714
- Scherer, K. R. (1999). Appraisal theories. In T. Dalgleish, & M. Power (Eds.), *Handbook of cognition and emotion* (pp. 637–663). Chichester, UK: Wiley.
- Schneider, D., Tschopel, S., & Schwenninger, J. (2012, May 23-25). Social recommendation using speech recognition: Sharing TV scenes in social networks. In *Proceedings of the 2012 13th International Workshop on Image Analysis for Multimedia Interactive Services (WIAMIS)* (pp. 1-4).
- Schroder, M., Baggia, P., Burkhardt, F., Pelachaud, C., Peter, C., & Zovato, E. (2011). Emotionml--An upcoming standard for representing emotions and related states. [ACII]. *Affective Computing and Intelligent Interaction*, *1*, 316–325. doi:10.1007/978-3-642-24600-5_35
- Schroder, M., Devillers, L., Karpouzis, K., Martin, J., Pelachaud, C., Peter, C., & Wilson, I. (2007). What should a generic emotion markup language be able to represent? *Lecture Notes in Computer Science*, *4738*, 440. doi:10.1007/978-3-540-74889-2_39

Schroder, M., Pirker, H., & Lamolle, M. (2006). First suggestions for an emotion annotation and representation language. In *Proceedings of LREC* (pp. 88-92).

Schröder, M., Wilson, I., Jarrold, W., Evans, D., Pelachaud, C., Zovato, E., & Karpouzis, K. (2008). What is most important for an emotion markup language? In *Proc. Third Workshop Emotion and Computing (KI 2008)*, Kaiserslautern, Germany.

Schröder, M., Wilson, I., Jarrold, W., Evans, D., Pelachaud, C., Zovato, E., & Karpouzis, K. (2008). What is most important for an emotion markup language? In *Proc. Third Workshop Emotion and Computing, KI 2008*, Kaiserslautern, Germany.

Soleymani, M. S., Chanel, C. G., Kierkels, J. K., & Pun, T. P. (2009). Affective characterization of movie scenes based on content analysis and physiological changes. *International Journal of Semantic Computing*, 3(2), 235–254. doi:10.1142/S1793351X09000744

Varela, M., Putnik, G., & Ribeiro, R. (2012). A web-based platform for collaborative manufacturing scheduling in a virtual enterprise. *Information and Communication Technologies for the Advanced Enterprise: An International Journal*, 2, 87–108.

William, J. (1950). *The principles of psychology* (Vol. 2). New York, NY: Dover Publications.

Wong, K., & Adamson, G. (2010). Part of the tool kit. [IJWP]. *International Journal of Web Portals*, 2(1), 37–44. doi:10.4018/jwp.2010010104

ENDNOTES

¹¹http://developer.nytimes.com/docs/movie_reviews_api

Eva Ferreira de Oliveira is currently a lecturer in the School Technology at the Polytechnic Institute of Cávado and Ave, Portugal. She holds a Dipl Eng in the field of information systems and information technologies and a MSci in the field of systems and informatics engineering both from University of Minho (Portugal). She teaches web development, interactive systems, and character animation to undergraduate students. Her scientific and research interest are related to new ways of visualizing and interacting with videos exploring affective dimensions.

Teresa Chambel is a professor and researcher at Faculty of Sciences, University of Lisbon (FCUL) in Portugal, where she received a Ph.D. in Informatics, on video, hypermedia and learning technologies, and a B.Sc. in Computer Science. Her M.Sc. was in Electrical and Computer Engineering at the Technical University of Lisbon, on distributed hypermedia. She is a member of the Human-Computer Interaction and Multimedia Group (HCIM) at the Lasige Lab at FCUL, since 1998, and was previously a member of the Multimedia and Interaction Techniques Group at INESC, Lisbon. Her research interests include multimedia and hypermedia, with a special emphasis on video and hypervideo, human-computer interaction, elearning, creativity, visualization, accessibility, cognition and emotions, interactive TV, digital talking books and digital art. For more information, visit: www.di.fc.ul.pt/~tc

Nuno Magalhães Ribeiro is Associate Professor at the Faculty of Science and Technology of Fernando Pessoa University (Porto, Portugal). He is the coordinator of the Computer Science area, being the course director for bachelor and masters courses on Computer Systems Engineering, specializations on Multimedia and Information Systems and Mobile Computing. Currently he teaches subjects on Multimedia and Interactive Systems, Multimedia Compression and Representation, Digital Design and Applied Electronics. He holds a Ph.D. on Computer Science by the University of York (U.K.), and an M.Sc. on Electrical and Electrotechnical Engineering, specialization on Telecommunications and a Licenciante degree on Electrical and Electrotechnical Engineering, specialization on Computer Systems, both by the Faculty of Engineering of the University of Porto (FEUP). He participated in international R&D projects developed at the Multimedia Center of the University of Porto (CMUP) and at the Institute of Computers and Systems Engineering (INESC). Currently, he is a researcher at the Center of Multimedia Studies and Resources (CEREM) at Fernando Pessoa University. His research interests lie on e-learning systems based on multimedia and mobile computing technologies, and he supervises Ph.D. projects on m-learning and emotion-based video search and retrieval. He is the author of the books Tecnologias de Compressão Multimédia (FCA) about multimedia compression and representation, Multimédia e Tecnologias Interactivas (FCA) about multimedia interactive systems and interfaces, and Informática e Competências Tecnológicas para a Sociedade da Informação (UFP) about general computer science.