

# Statistical Approach of User's Experience in the Visualization of Architectural Images in Different Environments

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## ABSTRACT

The visualization of images, both photographic and infographic, is a process that depends on a series of features that define the user (user profile: age, sex, experience), the visual message (type of image, resolution, quality), and the display (size, resolution, type of screen). When we can determine how the tree features relate, the communicative messages based on visual aspects will be more efficient for both the user and the technological output.

The main objective of the research work presented in this paper is to determine whether differences in the visualization of specific types of images related to the architecture framework, have significant statistic differences depending on the gender of the user. The reflection of the existence of such differences in the future will allow us to define the characteristics of the image and the display conditions to maximize the emotional communication depending on the type of user.

**Keywords:** Visualization; Immersive display; Architectural images; Emotional usability; User experience.

## 1. INTRODUCTION

In recent years, the new immersive techniques of visualization have led to the control of big volumes of increasingly complex multimedia information, therefore facilitating its analysis, interpretation, and manipulation [1, 31]. Also, the visualization of architectonic projects has gone through a fast evolution in recent years. The use of traditional photography and models has not been done away with as aesthetic resources used to check the space and shapes. But, increasingly, aside from these high-quality models, the use of infographic techniques has allowed the generation of images and animation, that let the professional or the architect, study details, change textures or illumination in a faster, more interactive, and comfortable way.

This work includes a multidisciplinary approach that aims to study the emotional response (affinity and activation) of a user according to the technique features of an image (color or black and white, and level of compression) and its display where it is visualized (immersive or not and the distance of visualization), in order to obtain some first approaches to the generation of images with correct parameters that will optimize the way the user visualize the architecture project.

To validate our results, we analyzed our data from a statistical point of view. This approach has reflected some significant

differences based on gender of users and their previous experience of viewing images of a specific framework.

## 2. IMAGE PERCEPTION AND VISUALIZATION

The generalized use of the digital image has been very popular during the last few years, especially on the Internet, where there are many image banks where users share millions of pictures every day, including Flickr, Getty Images, Fotosearch, and many more like them. This development has caused the constant study of new methods and applications to resolve the inclusion of descriptive parameters in the image, also known as metadata [17]. Most of the preferred methods [8,16,36] base their efforts in extracting automatically the descriptors that define the image from an objective point of view. That is, by describing the elements that compose the image [4, 12, 23, 33]. There are very few works that reflect the ideas or concepts unique to the user [18] and that personalize the result according to the user.

For our study, we have used a system similar to Flickr: the image is stored externally in the database, but remains linked to all valuations that users do when they visualize it. Our iconographic system allows an easy navigation by the user, regardless of the display, and allows us an easy analysis of the data stored in the image.

### Image perception

In a psychological area, we used works that would allow us to evaluate the differences of perception by the user [28], as well as measure the type and amount of emotions that the image provokes in the viewer [19]. We can find cultural differences as to how the user assigns different descriptors [26]. The interpretation of the colors, for instance, can have a direct influence on the emotions that the visual message generates in the viewer [38], and for this reason we believe that it is very important to find the best way to store them (the emotions).

Paul Ekman (one of the major recognised experts in the definition of emotions), has demonstrated that, by studying the facial expressions, these emotions are universal [10]. Simply put, they can be studied [9]:

- By the use of a scale “pleasant-unpleasant”
- By the use of a scale “active-passive”
- By studying cultural and social differences, as emotional reactions are learned in a specific environment

Centered in the field of psychology and neuropsychology, the main study of how the user reacts in front of an image is the IAPS (International Affective Picture System [30]), revised and replied in several studies to check out its validity within diverse cultural frameworks [3]. In the case of the original IAPS system, the emotions are grouped into three variables: “valence” or level of happiness; “activation” or level of excitement (also called arousal), and “dominance” or level of control sensation. This system is defined as an effective method to check out abnormal behavior and emotional dysfunction in several types of users [18, 20].

### Colour and Quality

The perception of color, as any other sense, is subordinated to subjective analysis criteria. Color depends on personal preferences, its relationship with other colors and shapes in the line of sight (contrast, expansion, received lighting, harmony with environment), the perceiver’s state of health, state of mind, and other factors. We should mention that some experts cite the Hypothesis of Linguistic Relativism (HRL), which states that language can affect the chromatic perception in some aspects, as different languages divide the spectrum received by the user in a different way [34].

Psychology and experimentation with colors and photographic image have confirmed the emotional influence that colors have on a user [2, 6, 19, 22, 29, 37, 38], including the differences between men and women and their cultural environment [24, 25]. On the other hand, we can find the quality perceived by the user. Nowadays, the study of quality perception in the image has generated great interest because of the benefits to business, and that has caused an increase in the research of this field [24, 35].

However, it is very difficult to define the concept of quality and measure it in an image. To start, it depends on the physiological aspects of each user [6], which gets more difficult when subjective aspects, such as society or culture of the user [32], are considered. The work of Peter Engeldrum [11], describes a systematic method called Image Quality Circle, IQC, which orders the main elements that define the image quality. Among these elements, we can find technological variables, physical parameters of an image, and finally, the human determining factors of the perception process that generates the rate of an image quality. The interconnection of these variables allows the creation of a “psychometric scale” based on the user appreciations, taking into account the different cultural variables. In order to work with users with the purpose of defining some scales of quality perception[24], it is necessary to define different stages:

- Psychophysical study to quantify the scales of perception. That is to say, the empiric study of models of human visual response, in which different concepts such as color, special and temporal sight, and different iterations, which lead to the final result, are related.
- Modeling of visualization to cover all stimuli.
- Iteration for verification.

Whereas we can study and understand the relationship between the different elements by which we can value the quality of an image perceived, we will get closer to being able to define all features that an image must have so that the exercise of a user’s visualization is satisfactory and could be adapted to all requirements [27]. The assertion is based on the work described in this paper.

### Immersive visualization

We can state that human vision is naturally immersive, as it places the individual in a specific environment. When we visualize a static image, this can be shown either in non-immersive display (TV, computer, mobile phone screens, etc.) or in immersive display (either projected in 2D showing the image in Head-Mounted Display (HMD), or in 3D in virtual reality display such as Binocular Omni-Oriented Monitors, ImmersaDesk, CAVE (Cave Automatic Virtual Environment [7]).

The user’s immersion allows the increase of peripheral vision, by increasing the communicative capacity of the environment and message, since the user is mentally absorbed by the environment [5]. But we need to know if this ability of the immersive display is affected by the characteristics of the image and the gender of the user. This is the initial hypothesis that we intend to explore in the following chapters.

### Statistical Approach

To analyze the data obtained, we must first classify the type of sample. This classification will determine the method of calculation if the difference between users is statistical significant. In our case, we have worked with disparate groups (also called “non-related” or independent samples), which means that the observations were carried out on different sampling units with separate average.

The first step is to define the level of significance ( $\alpha$ ). This level is used both for comparison of averages for assessing the level of confidence of a sample (based on an error rate selected). Usually working with values equal to or greater than 80% ( $\alpha = 0.2$ ), with normal values of 90 or 95% ( $\alpha =$  between 0.1 and 0.05), as values that most reduce the error sample.

The second step is to define the method of calculating the difference between two averages. The most common is the calculation of the “Student’s t-distribution” and the “Student’s t-test”. However, the formula varies depending on the number of samples, the typology, and finally by the variance between them. Calculated the variance between different averages to compare, we observed that this value was different, so to calculate both t-distribution and its probability we take into account this information (for example, Microsoft Excel has different methods to calculate t-distribution and t-test based on if valence of two samples is the same or not). If the order of comparison between averages is relevant, we need to cut the distribution by one sided, while if the order is not relevant we will use the two sided method (this last situation is that we find in our study case).

## 3. INTERACTION RESULTS

### Methodology

We have generated a new web application of easy-use classification for both expert and non-expert users. It is also, easy to learn, allowing image indexing from the personal valuation of users, so that we can extract any user-related information from any device with an Internet connection. To achieve it, we have developed a system based on Open Source technology [13].

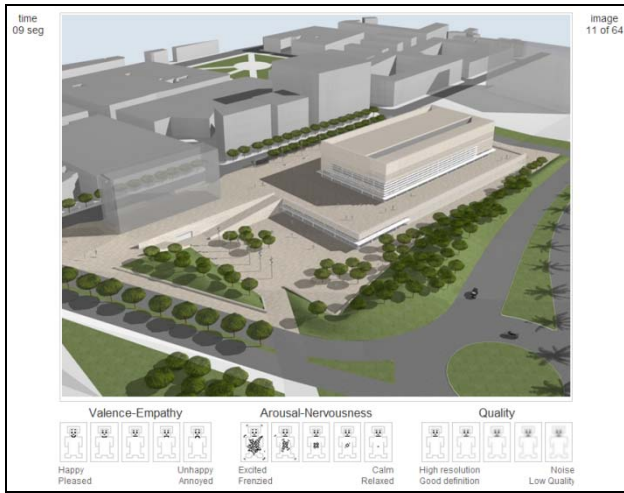


Figure 1.- Screenshot Test Webpage

To generate an empiric approach in the visualization phase of architectural images, incorporating concepts, methodologies, and measurement techniques that are well established in media psychology and user-centered studies, we have divided our work into three phases:

- Phase 1: Replication and valuation of the IAPS model and the on-line test system of the project.[14].
- Phase 2: Implementation of a model combining original images of the IAPS and images modified in color and compression [15].
- Phase 3: Implementation of a model combining images of the second phase (such as “control images”) and original images related to architecture (infographic, phototypesetting, and real images of projects). Architectural images have been presented both as originals and as the same type of compression and color-modification as the images of stage 2.

**Study Phase: Number 3, evaluation of architecture image and immersive environment**

This test has been carried out in two environments: the first one (not immersive) with a computer screen (12 women, A:27,7 - SD:7,2 and 22 men, Av:28,86 - SD:7,01).



Figure 2.- Users realizing test on Computer Screen

The second one was with an immersive screen (Head Mounted Display, HMD) in our laboratory (6 women, A:25,83 - SD:6,36 and 8 men, Av:27,25, SD:6,45).



Figure 3.- Users realizing test on HMD

The typology of users who carried out test number three was: teachers, students, and professionals of the architecture

framework: and other users who are unrelated to the field. We took into consideration the resolution of the screen, visualization distance and image size, information that we will later use to study in depth the importance that the above mentioned parameters have in the visualization action. The value of the estimated error for this phase was 1.6% on the total sample of 2.980 valid punctuations, bearing in mind the response time of the user, and the variables that have remained without validating every image.

**Main Results**

The first experiment carried out was to observe the quality perceived by users in the specific case of images with a high compression level (JPG2000 black and white photographic images with a compression level of 95% equivalent to a bit rate of 0.05, according to the procedure of the previous phases).

The results show us a clear difference in the visualization between male and female as we can see in the following figure:

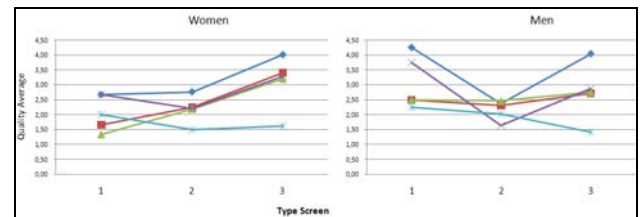


Figure 4. Quality Perceive (6 JPG2000 images in B&W High Compression) by gender in three environments: 1: HMD, 2: Computer Screen, 3: Projector Screen

The quality perceived by women is higher viewing a large display with standard quality (reaffirming the initial study of the phase 2), while on close-up displays (computer screen and HMD) the average of perceived quality of the same images is lower. The behavior of women corresponds more closely to the expected model: When the image is visualized at a very short distance, pixels and the possible errors of compression are more easily perceived and the quality perceived decreased.

The male behavior is an interesting case study. This group perceives the image with more quality in the screen (HMD) with minus resolution (HMD: 800x600, projector: 1024x768, computer: 1280x1024) with results very close to the projector screen. The visualization on a computer screen is where they perceive pixel details and compression errors more clearly, resulting in lower marks in comparison with the other environments. Also, we can observe (reaffirming previous results) that the quality perceived is directly related to the happiness and nervousness levels of the users (valence and arousal levels in the IAPS System):

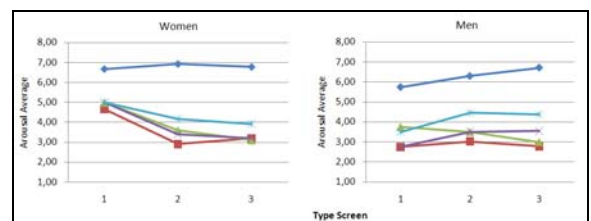


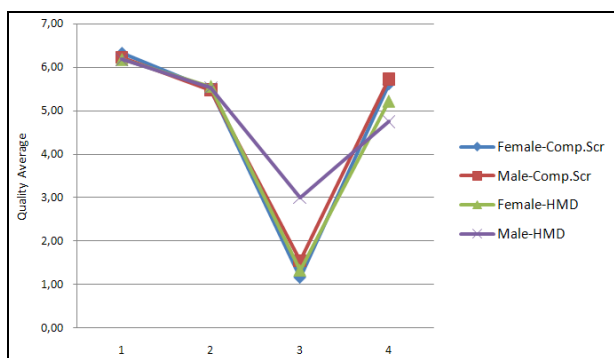
Figure 5. Arousal Average (6 JPG2000 images in B&W High Compression) by gender in three environments: 1: HMD, 2: Computer Screen, 3: Projector Screen

In the previous figure we can see that for both men and women, a higher perceived quality leads to a decrease in the level of

nervousness of the user, which results in greater empathy with the displayed image.

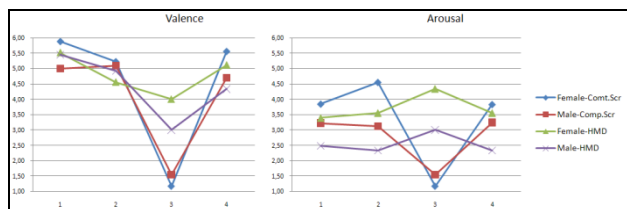
The second study was focused on the evaluation of computer-generated architectural images (also known as infographic images). We studied two environments (computer screen and HMD) with four types of images: JPG color original, color images compressed in JPG2000 with 80% and 95% rates, and finally uncompressed images in JPG, but in black and white.

As predicted, the perceived quality decreases according to the level of compression (Figure 6). Further significant observations include the reduction of the quality perceived in the case of uncompressed B&W images (computer screen average:5,67-SD:0,24; HMD average:4,99-SD:0,26) compared to the same images in color (CS\_Av:6,28-SD:0,34; HMD\_Av:6,18-SD:0,48) and that the above mentioned decrease is more accentuated in HMD visualization (23,97 %) than with the computer screen (10,67 %).



**Figure 6. Quality perceived at infographic images. 1: Color without compression, 2: Color with 80% compression, 3: Color with 95% compression, 4: B&W without compression**

If we look at emotional behavior according to gender of users we obtain the following results:



**Figure 7. Valence and Arousal at infographic images. 1: Color without compression, 2: Color with 80% compression, 3: Color with 95% compression, 4: B&W without compression**

As we can see, the behavior of the valence is similar to the quality perceived (which reaffirms their direct relation). Moreover, there is a clear emotional difference based on the display of visualization and that is corroborated when the information of the arousal is studied.

The visualization in an immersive environment reduces the loss (more than 8%) of the valence (Av:4,61-SD:0,78) with regard to computer screen visualization (Av:4,27-SD:0,41), which maintains a direct relation with the perceived quality.

Computer screen arousal follows the graphs of valence and quality, so we can affirm that there is a direct relationship between them, whereas in the case of immersive visualization we might conclude that the loss of quality observed generates a major excitement with a high decrease of the valence.

## Statistical Results

The first analysis was to evaluate the difference of valence in women based on their previous experience viewing architectural contents (variable 1: with experience, variable 2: without experience). This first study was conducted with data from the computer screen display:

	Variable 1	Variable 2		
Significance Level	$\alpha = 0.05$		$\alpha = 0.1$	$\alpha = 0.2$
Average	5,87024	5,525913		
Variance	0,31769	0,098505		
Number of test	7	5		
Degrees of freedom	10			
t-distribution	1,34969			
P(T<=t) one sided	0,10344			
Critic value of t (one sided)	1,81246		1,3722	0,8791
P(T<=t) two sided	0,20687			
Critic value of t (two sided)	2,22814		1,8125	1,3722

**Table 1. Student's t-distribution with difference variance of valence on computer screen visualization. Female users.**

Therefore, for this example and the next ones, we use a significance level of  $\alpha = 0.2$ , since we have a relatively small number of samples and it is equate to  $\alpha = 0.1$  for an ordered comparison (i.e. cutting by one sided the t-distribution [39]).

	PC-Act	PC-Qlty	HMD-Val	HMD-Act	HMD-Qlty
Significance Level	$\alpha = 0.2$				
t-distribution	-0,8	-0,4	-0,6	-0,2	-1,2
P(T<=t) one sided	0,20	0,32	0,32	0,41	0,15
Critic value of t (one sided)	0,89	0,88	1,38	0,94	0,98
P(T<=t) two sided	0,41	0,65	0,63	0,83	0,3
Critic value of t (two sided)	1,41	1,38	3,08	1,53	1,64

**Table 2. Student's t-distribution with difference variance of valence, arousal and quality on computer screen and HMD. Female users.**

For  $\alpha = 0.2$  we conclude that there is only a significant difference in valence level based on the experience of female users viewing our images on computer screen (Table 1). The other levels and in HMD environment we do not find significant differences.

Next, we can see the results of compare the behavior of male users:

	PC-Val	PC-Act	PC-Qlty	HMD-Val	HMD-Act	HMD-Qlty
Significance Level	$\alpha = 0.2$					
t-distribution	1,47	-1,40	0,97	0,92	-0,94	1,27
P(T<=t) one sided	0,07	0,08	0,17	0,26	0,19	0,21
Critic value of t (one sided)	0,86	0,85	0,86	1,37	0,90	1,37
P(T<=t) two sided	0,15	0,17	0,34	0,52	0,38	0,42
Critic value of t (two sided)	1,33	1,32	1,33	3,07	1,43	3,07

**Table 3. Student's t-distribution with difference variance of valence, arousal and quality on computer screen and HMD. Male users.**

Clustering results (both those from computer screen as HMD and by gender), and evaluating the difference of previous experience of the users, we have the following results:

	Valence		Arousal		Quality	
	ARQ	No ARQ	ARQ	No ARQ	ARQ	No ARQ
Average	5,596	5,113	3,130	3,855	6,068	5,766
Variance	0,454	1,151	2,442	1,043	1,608	1,924
Number of test	28	20	28	20	28	20
Degrees of freedom	30		46		39	
t-distribution	1,7768		-1,9419		0,7715	
P(T<=t) one sided	0,0428		0,0291		0,2225	
Critic value of t (one sided)	0,8537		0,8495		0,8509	
P(T<=t) two sided	0,0857		0,0582		0,4450	
Critic value of t (two sided)	1,3104		1,3002		1,3036	

**Table 4. Student's t-distribution of all users and environments compared by previous experience.**

#### 4. CONCLUSION

In architectural project visualization and with images in general, we can distinguish the behavior of the users according to gender. Women perceive images with a better quality in not immersive and common environments (visualization in projector screen), while men value the perceived quality more highly in immersive environments (HMD). These data support the conclusion that the generation of images for a particular customer and for a particular display must take into account such variables for a streamlined communications experience.

A direct relation exists between the perceived quality and the emotional evaluation of the image by the user. While the user does not perceive a quality loss, values the image with a high valence (in an independent way to the semantic category in the one that circumscribes the image), the perception of the errors of compression reduces the "affinity" with the image and increases the activation of the user (especially for the women). This behavior is more notable in immersive environment in comparison with classic visualization situations.

The visualization of black and white images of architectural projects generates lower values than color images of equal resolution and quality of compression, generating in turn a decreased emotional response with respect to the project in color.

The compression of infographic images must be much more restrictive than for photographic images, since at equal levels of compression (from JPG to JPG2000 to 80%), both the evaluation of the quality and the valence is lower when compared to photographic images. This observation, not only supports the values but, according to the typology of the image, it increases them. This situation is due to the fact that the image generated by computer "lacks realistic imperfections" which correspond to the real image, being more sensitive to the errors produced by the "pixelation" or the compression.

There is a statistically significant difference in the emotional assessment of architectural images for both men and women in the computer screen environment based on past experience viewing this type of images. This data would allow us to conclude that in high resolution environments is most evident differential behavior of the users based on their previous experience with the type of images displayed.

Finally, we conclude that it has been found that previous experience in a specific thematic images viewing experience, directly affects the emotional behavior of users, reaching a significant level of around 95% (see Table 4).

#### 5. REFERENCES

[1]. André, E. **The Generation of Multimedia Presentations.** *A Handbokk of Natural Language Processing: techniques and applications for the processing of language as text.* Marcel Dekker Inc., 2000, págs. 305-327.

[2]. Berlin, B., Kay, P. **Basic Color Terms: Their Universality and Evolution.** *Berkeley: University of California Press,* 1969.

[3]. Bruno Verschuere, Geert Crombez, Ernst Koster. (2007). *Cross Cultural Validation of the IAPS.* Ghent, Belgium: Ghent University.

[4]. Chang, S-K., Hsu, A. **Image Information Systems: Where do we go from here.** *IEEE Educational Activities*

*Department, 1992. IEEE Transactions on knowledge and data engineering.* Pittsburg Vol. 4, pp. 431-442.

[5]. Charles Henden, et al. **A sorround display warp-mesh utility to enhance player engagement.** *ICEC Proceedings.* Carnegie Mellon University Entertainment Technology Center, 2008.

[6]. Coursaris, C.K., Swierenga, S.J., Watrall, E. **An Empirical Investigation of Color Temperature and Gender Effects on Web Aesthetic.** *Journal of Usability Studies, Vol. 3* 2008, págs. 103-117.

[7]. Cruz-Neira, C., Sandin, D. J., DeFanti, T. A. **Surround-screen projection-based virtual reality: the design and implementation of the CAVE.** *ACM press 1993. Proceedings of the 20th annual conference on computer graphics and interactive techniques.* págs. 135-142.

[8]. Eakins, John P., **Towards intelligent image retrieval.** *Pattern Recognition Society.* 35, Elsevier Science Ltd, 2002, Pattern Recognition, págs. 3-14.

[9]. Ekman Paul. **A methodological discussion of nonverbal behavior,** *Journal of Psychology,* 1957, 43, 141-149.

[10]. Ekman Paul. **Facial Expressions of emotion,** 1979

[11]. Engeldrum, Peter. **A Theory of Image Quality: The Image Quality Circle.** *Journal of Imaging Science and Technology, Vol. 48,* págs. 446-456 USA , 2004.

[12]. Enser, Peter. **Visual image retrieval: seeking the alliance of concept-based and content-based paradigms.** *Journal of Information Science, Vol. 26.* 2000, págs. 199-210.

[13]. David Fonseca, Oscar Garcia, Isidro Navarro, Jaume Duran, Eva Villegas, Marc Pifarre, Xavier Sorribes. **Iconographic WEB image classification based on Open Source Technology.** *Proceedings of the 13th World Multi-Conference on Systemics, Cybernetics and Informatics 2009 (WMSCI09).* Vol. 3, págs. 184-189. Orlando, USA.

[14]. Fonseca, D., Fernández, J.A., Garcia, O. **Comportamiento Plausible de agente virtuales: Inclusión de parámetros de usabilidad emocional a partir de imágenes fotográficas.** *Memorias CИСCI 2007.* Vol. 1, págs. 147-152. Orlando, USA.

[15]. David Fonseca, Oscar Garcia, Jaume Duran, Marc Pifarre, Eva Villegas. **An Image-Centred Search and Indexation System based in User's Data and Perceived Emotion.** *ACM, 2008. ACM International Conference on Multimedia. 3rd International Workshop on Human-Centered Computing (HCC).* Vancouver : págs. 27-34.

[16]. Gupta, A., Jain, R. **Visual information Retrieval.** *Communications of the ACM, 1997.* New York :Vol. 40, pp. 69-79.

[17]. Henry Lieberman & Hugo Liu. **Adaptative Linking between Text and Photos Using Common Sense Reasoning.** *Second International Conference AH 2002, Lecture Notes in Computer Science 2347.* Malaga, Spain : Springer 2002, pp. 2-11.

[18]. L. Hollink, A.Th, Schreiber, B.J. Wielinga, M. Worryng. **Classification of user image descriptions.** *International Journal of Human-Computer Studies, Vol. 61,* Elsevier Ltd. - Academic Press, Inc, 2004, págs. 601-626.

[19]. Hong, S., Ahn, C., Nah, Y., Choi, L. **Searching Color Images by Emotional Concepts.** *3rd International Conference on Human.Society@Internet,* Tokyo, Japan, July 27-29, 2005. Springer Vol. 3597/2005.

[20]. Houtveen JH, Rietveld S, Schoutrop M, Spiering M, Brosschot JF. (2001). A repressive coping style and affective, facial and physiological responses to looking at emotional pictures. *International Journal of Psychophysiology,* 42, 265-277.

[21]. Itziar Fernández, Pilar Carrera, Flor Sánchez, Darío Paéz. **Prototipos emocionales desde una perspectiva cultural.**



- [22]. Li-Chen, Ou. **World of Colour Emotion**. 2006. <http://colour-emotion.co.uk/whats.html>
- [23]. Lim, J.-H., Jin, J.S. **A structured learning framework for content-based image indexing and visual query**. *Multimedia Systems, Vol. 10*. Springer Berlin / Heidelberg, 2005.
- [24]. Mark D, Fairchild. **Image quality measurement and modeling for digital photography**. *Tokyo 2002. ICIS*. págs. 318-319.
- [25]. M<sup>a</sup> del Carmen Porras, Martha M. Pereyra. **El valor psicológico del color y su uso en la comunicación**. *HUELLAS-Búsquedas en Artes y Diseño, págs. 141-145* 2001.
- [26]. Mikels, Fredrickson, Larkin, Lindberg, Maglio, Reuter-Lorenz. (2005). Emotional category data on images from the IAPS. *Behaviour Research Methods*, 37 (4), 626-630.
- [27]. Nam, J., Yong M. R., Huh, Y., Kim, M. **Visual Content Adaptation According to User Perception Characteristics**. 2005, *IEEE Transactions on Multimedia*, Vol. 7, págs. 435-446.
- [28]. Pask, A. M. (2005). Art Historians' Use of Digital Images: a Usability Test of ARTstor. A Master's Paper for the M.S. in L.S. degree.
- [29]. Peggy Wright, Diane Mosser-Wooley, Bruce Wooley **Técnicas y Herramientas para Usar Color en el Diseño de la Interfaz de una Computadora**. 1999, *ACM - Crossroads. Interacción Humano - Computadora*.
- [30]. Peter J. Lang, Margaret M. Bradley & Bruce N. Cuthbert. (2005). International Affective Picture System: Affective ratings of pictures and instruction manual. University of Florida, NIME. Gainesville: University of Florida.
- [31]. Robbe-Reiter, et. Al. **Expression constraints in multimodal human-computer interaction**. *Intelligent User Interfaces*. New Orleans , 2000, págs. 225-228.
- [32]. Tractinsky, Noam **Aesthetics and Apparent Usability: Empirically Assessing Cultural and Methodological Issues** *ACM CHI 97 Electronic Publications: Papers* Atlanta
- [33]. Tsai, C.-F., McGarry, K., Tait, J. **Qualitative evaluation of automatic assignment of keywords to images**. *Information Processing & Management, Vol. 42*. Sunderland (UK) : Elsevier Ltd., 2004.
- [34]. Valenzuela, Javier, **Sobre colores y lenguas**. *Ciencia Cognitiva - Revista electrónica de divulgación* 2008, Vol. 2, págs. 56-58.
- [35]. Vansteenkiste E., Van der Weken D., Philips W., Kerre E **Perceived image quality measurement of state-of-the-art noise reduction schemes**. *Lecture Notes in computer science, 2006, Advanced concepts for intelligent vision systems proceedings*, Vol. 4179, págs. 114-126.
- [36]. Venkat, N.G., Vijay, V.R. **Modeling and retrieving images by content**. *Information Processing & Management / COMPUTER (1995)*, Elsevier Science Ltd., 1997, Vol. 33, pp. 427-452.
- [37]. Xiaodi Hou, Liqing Zhang. **Color Conceptualization**. *15th International Multimedia Conference ACM, 2007* Augsburg.
- [38]. J. H. Xin 1, K. M. Cheng, G. Taylor, T. Sato, A. Hansuebsai **Cross-Regional Comparison of Colour Emotions Part I. Quantitative Analysis**. *Color Research & Application, Vol. 29, pp. 451-457*. Wiley Periodical Inc., 2004,
- [39]. Wikipedia, Student's t-distribution, Edited and Consulted October 2010. [http://en.wikipedia.org/wiki/Student%27s\\_t-distribution](http://en.wikipedia.org/wiki/Student%27s_t-distribution)