EVALUATION OF FEATURES AND COMBINATION APPROACHES FOR THE CLASSIFICATION OF EMOTIONAL SEMANTICS IN IMAGES

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Abstract: Recognition of emotional semantics in images is a new and very challenging research direction that gains more and more attention in the research community. As an emerging topic, publications remains relatively rare and numerous issues need to be addressed. In this paper, we propose to investigate the efficiency of different types of features including low-level features and proposed semantic features for classification of emotional semantics in images. Moreover, we propose a new approach that combines different classifiers based on Dempster-Shafer's theory of evidence, which has the ability to handle ambiguous and uncertain knowledge such as the properties of emotions. Experiments driven on the International Affective Picture System (IAPS) image databases, which is a common stimulus set frequently used in emotion psychology research, demonstrated that the proposed approach can achieve promising results.

1 INTRODUCTION

In recent years, online photo sharing communities are emerged and are growing (like, flick.com, photo.net, dpchallenge.com, deviantart.com). In the era of information explosion especially with more and more pictures and other multimedia, it is an urgent thing to continuously develop intelligent systems for automatic image emotional semantic analysis.(A. W. M Smeulders, 2000; R. Datta, 2005)

One of the goals of computer science, and particularly artificial intelligence is to elaborate intelligent computers having the ability to interact with human beings in a natural way. Thus, one of key issues is to allow computers to recognize, understand and express emotions, and numerous works have been done for recent years on these aspects (J. Z.Wang, 2001; K. Kuroda, 2002; Picard, 1997; C. Columbo, 1999; C.-H. Chan, 2005; S. Wang, 2005; C.-T. Li, 2007; Z. Zeng, 2009; W. Wang, 2008).

As far as emotion recognition is concerned, researches mainly focus on affect recognition in audio (speech and music) and visual based facial expressions. Limited contributions deal with the recognition of emotions carried by images (V.Yanulevskaya, 2008; W. Wei-ning, 2006; S. Wang, 2005; Q. Wu, 2005; C. Columbo, 1999), and a lot of issues need to be addressed particularly concerning the three following fundamental problems: emotion models, feature extraction for emotion recognition and classification schemes to handle the distinctive characteristics of emotions, and the main difficulty remains to bridge the gap between low-level features extracted from images and high level semantic concepts such as emotions.

Several models have been considered in the literature to represent emotions (P. Dunker, 2009), and the two main approaches are the discrete one and the dimensional one. The first model consists in considering adjectives or nouns to specify the emotions, such as happiness, sadness, fear, anger, disgust and surprise. The second model describes emotions accord-

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ing to one or more dimensions representing a special mood characteristic, such as pleasure, arousal or control. These models allow representing a wider range of emotions than the first one. In this paper, the dimensional model has been employed as illustrated in Fig. 1.

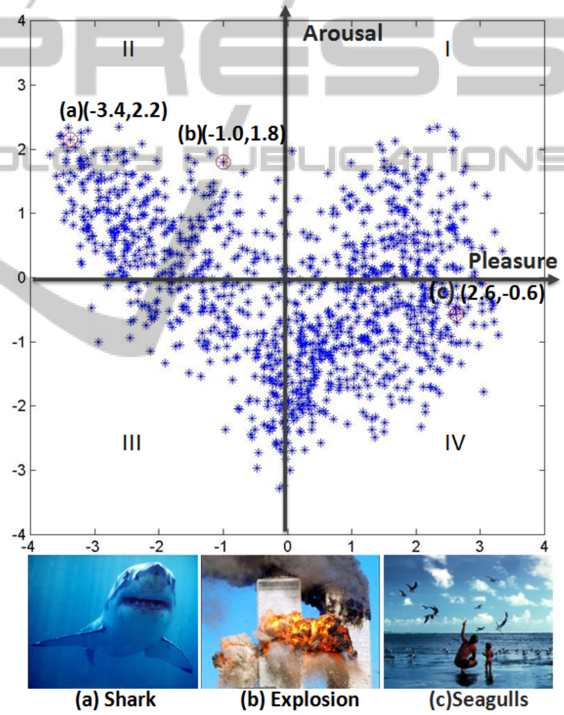
Few works have been done to propose an efficient automatic images emotion recognition system. Yanulevskaya et al. (V.Yanulevskaya, 2008) propose an emotion categorization approach for art works based on the assessment of local image statistics using support vector machines. Wang et al. (S. Wang, 2005) uses a Support Vector Machine of Regression to predict values of emotional factors based on three image features: luminance fuzzy histogram, saturation fuzzy histogram integrated with color contrast and luminance contrast integrated with edge sharpness. Colombo et al. (C. Columbo, 1999) use a suitable set of rules to extract some intermediate semantic levels, and then build the semantic representation by a process of syntactic construction called compositional semantics. Wu et al. (Q. Wu, 2005) use SVMs to learn the mapping correlation between affective space and visual feature space of images, and then the trained SVMs are used to estimate and classify images automatically. However, no study has attempted to identify the most adapted features and type of classifiers to handle the characteristics of emotions which are high-level semantic concepts. Thus, we propose in this paper to evaluate the efficiency of different types of features and combination methods for emotion recognition. Moreover, we present a novel combination approach based on Dempster-Shafer's Theory of Evidence, which allows to handle ambiguity and uncertainty which are characteristics of emotions.

The rest of this paper is organized as follows. Image features used for characterizing emotions in images are presented in section 2. The proposed fusion of information based on the Theory of Evidence is detailed in section 3. Experiments setup and results are presented in section 4, followed by the conclusion in section 5.

2 IMAGE FEATURES FOR EMOTION CLASSIFICATION

2.1 Low-level Image Features

Most of works dealing with emotion recognition make use of traditional image features that are also used for other computer vision problems. The three main categories of image features are based on color, texture and shape informations. Concerning color, studies have shown that HSV (Hue, Saturation, Value) color space is more related to human color perception than others such as RGB color space. Based on HSV color space, authors (P. Dunker, 2009; Q. Wu, 2005) use several ways to describe color contents in images such as moments of color, color histograms, correlograms and histograms of color temperature. Concerning texture, Tamura features (Q. Wu, 2005) have been proven to correlate strongly with human visual perception: coarseness, contrast, directionality. The spatial grey-level difference statistics (C.-T. Li, 2007), known as co- occurrence matrix, can describe the brightness relationship of pixels within neighbourhoods, and the local binary pattern (LBP) descriptor is a powerful feature for image texture classification.



(a) Shark (b) Explosion (c)Seagulls

Figure 1: A dimensional emotion model: dimension of pleasure (ranging from pleasant to unpleasant) and arousal (ranging from calm to excited). Each point represents an image from database IAPS (P. J. Lang, 1999).

Concerning shape, studies on artistic paintings have brought to the fore semantic meanings of shape and lines, and it is believed that shapes in a picture also influence the degree of aesthetic beauty perceived by humans (Q. Wu, 2005). In this paper, the hough transform is employed to build a histogram of line orientations in 12 different orientations.

2.2 Semantic Image Features

Some attempts have been made to identify higher level image features linked to emotions. Thus, studies on artistic paintings have brought to the fore semantic meanings of color and lines that have been used for designing image features for emotion recognition purposes in the work of (C. Columbo, 1999). Indeed, color combinations can produce effects such as harmony, non-harmony, calmness and excitation. The visual harmony can be obtained by combining hues and saturations so that an effect of stability on human eye can be produced. This harmony can be represented thanks to Itten's chromatic circle (Itten, 1961) where colors are organized into a chromatic circle and contrasting colors have opposite coordinates according to the center of the circle (Fig. 2). To extract an image feature that characterizes harmony, dominant colors in the image are first identified and plotted into the chromatic circle. Then, the polygon linking these colors is considered. The harmony can finally be described by a value in such a way that a value next to 1 corresponds to a regular polygon whose center is next to the circle center which characterizes a harmonious image, and a value next to 0 corresponds to an irregular polygon characterizing a non harmonious image.

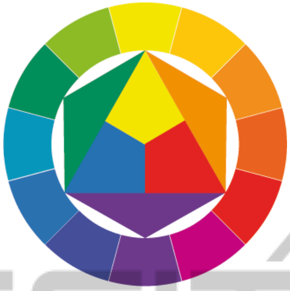


Figure 2: Itten's chromatic circle.

Lines also carry important semantic information in images: oblique lines communicate dynamism and action whereas horizontal or vertical lines rather communicate calmness and relaxation. To characterize dynamism and action in images, the ratio is computed between the numbers of oblique lines respect to the total number of lines in an image.

3 THE THEORY OF EVIDENCE FOR EMOTION RECOGNITION

Emotions are high-level semantic concepts that are by nature highly subjective and ambiguous. Thus, in order to perform efficiently this recognition task, it is necessary to handle informations that can be uncertain, incomplete, ambiguous and leading to conflicts, this paper attempts to solve this issue by proposing a new technique based on the Theory of Evidence.

3.1 Fundamentals of the Theory of Evidence

The Theory of Evidence (Dempster, 1968) introduced by Dempster and then formalized by Shafer (Shafer, 1976) and Smets(Smets, 1990) offers a theory allowing the reasoning on knowledge that can be uncertain, incomplete, and leading to conflicts.

Let $\Omega = \{H_1, H_2, \ldots, H_n\}$ be a finite set of possible hypotheses. This set is referred to as the frame of discernment, and its power set denoted by 2^{Ω}. Following are the basic concepts of the theory:

Belief Mass Functions. The confidence, or belief, we can have in a hypothesis given a source of information (a type of feature in our case) is expressed by the mass function m associated to this source of information. Thus, the mass function assigns a value in [0, 1] to every subset A of Ω and satisfies the following:

$$m^{\Omega}(\emptyset) = 0 \quad and \quad \sum_{A \subseteq \Omega} m^{\Omega}(A) = 1 \qquad (1)$$

Combination Rule. Different mass functions from several sources of information can be combined to improve the knowledge used for the classification decision. Let m_{S1}^{Ω} and m_{S1}^{Ω} be two mass functions from two independent sources of information $S1$ and $S2$. Then, the Transferable Belief Model (TBM) (Smets, 1990) combined mass function $m_{S1 \cap S2}^{\Omega}$ of an hypothesis $A \subseteq \Omega$ is given by:

$$m_{S1 \oplus S2}^{\Omega}(A) = \frac{\sum_{B \cap C = A} m_{S1}^{\Omega}(B).m_{S2}^{\Omega}(C)}{1 - m_{S1 \oplus S2}^{\Omega}(\emptyset)} \qquad (2)$$

where $m_{S1 \oplus S2}^{\Omega}(\emptyset) = \sum_{B \cap C = \emptyset} m_{S1}^{\Omega}(B).m_{S2}^{\Omega}(C)$

3.2 Computation of the Evidence

We propose in this paper an original approach for computing evidence. The principle is as follows. For each type of feature, considered as source of information S_j, SVM classifiers are first trained to recognize each of the classes, or hypotheses H_i. The outputs of these classifiers are used to compute the beliefs. This is done by applying on them membership functions, represented in Fig. 3 allowing to give a belief to the different classes and combination of classes, according to classifiers. However, the classifiers are not perfect and can be mistaken. To integrate this, the

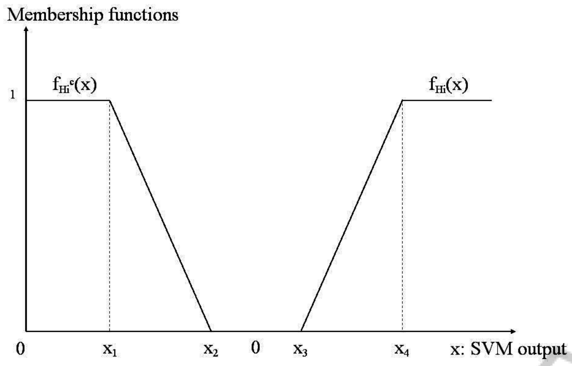


Figure 3: Membership functions f_{H_i} and $f_{H_i^c}$, associated respectively to classes H_i and H_i^c, applied on SVM output x to build mass functions.

efficiency of the classifiers (i.e. precision, given by the confusion matrix) is used to weight their decision. This is formalized as follows.

Let S_1, S_j, S_m be the m sets of features considered as sources of information. For all S_j, n binary classifiers c_{ij} are trained to recognize the n classes H_i. Let now consider the building of the mass function $m_{c_{ij}}$ corresponding to the belief mass obtained from source of information S_j using classifier c_{ij} trained to recognize class H_i. According to the output x_{ij} of c_{ij}, and using membership functions (Fig. 3), the mass is distributed on three subsets of Ω: Ω itself, H_i and H_i^c the complement of H_i in Ω as in Eq. 5.

$$m_{c_{ij}}(H_i) = f_{H_i}(x).p_{c_{ij}}(H_i) \tag{3}$$

$$m_{c_{ij}}(H_i^c) = f_{H_i^c}(x).p_{c_{ij}}(H_i^c) \tag{4}$$

$$m_{c_{ij}}(\Omega) = 1 - m_{c_{ij}}(H_i) - m_{c_{ij}}(H_i^c) \tag{5}$$

where $p_{c_{ij}}(H_i)$ is the precision of c_{ij} for class H_i and $p_{c_{ij}}(H_i^c)$ is the precision of c_{ij} for class H_i^c, both computed from the confusion matrix of c_{ij}.

Thus, if the output x of classifier c_{ij} is a high positive value, it means that c_{ij} is sure that the input is in class H_i. But, as c_{ij} may be mistaken, the mass is distributed not only on H_i but also on Ω which corresponds to uncertainty, according to the ability of c_{ij} to correctly recognize H_i. On the contrary, if x is very negative, it means that c_{ij} is sure that the input is in class H_i^c. However, this decision is also weighted by the ability of c_{ij} to correctly recognize H_i^c, leading to a distribution of mass between H_i^c and Ω. Finally, if x is around 0, it means that classifier c_{ij} has a doubt, thus the mass is in majority given to Ω, which corresponds to uncertainty.

Once mass functions $m_{c_{ij}}$ are computed from all classifiers c_{ij}, they are combined according to a given combination operator, such as Dempster's one (Eq.2), which corresponds to a fusion of informations given by all sources S_j. Finally, a single mass function is obtained distributing the belief over some subsets of Ω. The final decision can be taken according to decision measures presented in section 3.1.

4 EXPERIMENTS

In our experiments, we have made used of the IAPS database (P. J. Lang, 1999), which provides ratings of affect (pleasure or valence, arousal and control) for 1192 emotionally-evocative images. We have considered an emotion model based on the pleasure and arousal dimensions using four classes corresponding to each quadrant as shown in Fig. 5. The IAPS corpus is partitioned into a train set (80% of the data, 953 images) and a test set (20% of the data, 239 images), and all the experiments repeated ten times to get the average correct classification rate (CR).

To explore the performance of different feature sets for visual emotion recognition presented in Section 2, we have built a classification scheme using two support vector machine classifiers to identify each class: the first one is to identify arousal dimension, and the second one is dedicated to the pleasure dimension. The results obtained are shown in Figure 6.

From these results, it appears that among the different features, texture (LBP, Tamura) are the most efficient ones. Moreover, the higher level features (dynamism and harmony) may first seem giving lower performance, but as they consist in a single value, their efficiency is in fact remarkable.

To evaluate the efficiency of different types of combination approaches, we have built an emotion classification scheme that combined classifiers based on different features according to the framework illustrated in Fig. 4. In these systems, SVM classifiers are employed and each feature set S_j was used to train classifiers c_{ij}, which produces measurement vector y_{ij} corresponding to the probability of inputs to belong to different classes C_i. Vectors y_{ij} are then used to perform the combination to get the classification results according to section 3.2. The following combination methods have been implemented and compared to our approach based on the Theory of Evidence: maximum-score, minimum-score, mean-score and majority-score. The results obtained are shown in Table 1.

These results show that fusion with the Theory of Evidence is more efficient with an average percentage of 54.7% compared to fusion with mean-score, min-score, max-score, and majority voting, according to following equation (Robert Snelick, 2005) , which proves the ability of the Theory of Evidence to com-

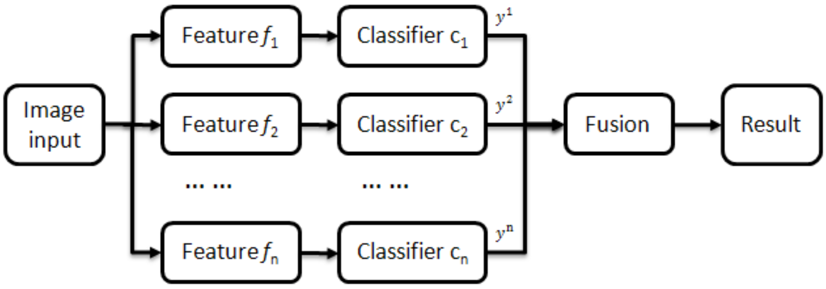


Figure 4: The classification scheme, which combined different classifier outputs.

Table 1: The accuracy for four classes, performed by the different fusion methods.

	Max score	*Min score*	*Mean score*	*Majority voting*	*Proposed combined*
I	56.32	51.25	50.87	55.20	58.97
II	53.08	50.24	52.51	53.36	55.00
III	52.67	48.31	50.43	47.37	51.76
IV	50.34	51.42	53.67	52.30	53.08
CR	51.87	50.31	53.10	52.05	54.70

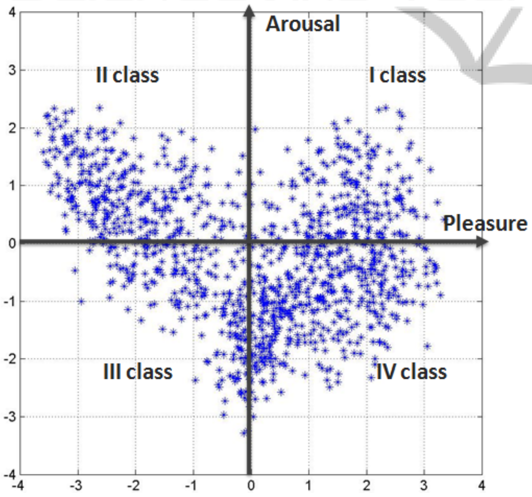


Figure 5: The dimensional emotion model is used to define 4 classes of emotions corresponding to the 4 quadrants.

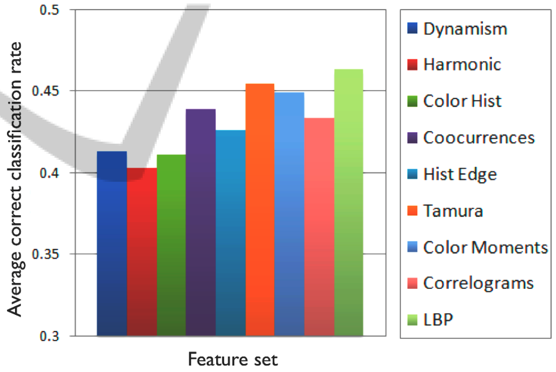


Figure 6: The average correct classification rate obtained using individual feature set.

bine the different sources of information and to exploit their complementarities.

$$Z(i) = \frac{1}{N}\sum_{n=1}^{N} y_i^n.\forall i. \qquad (6)$$

$$Z(i) = min(y_i^1, y_i^2, ..., y_i^N), \forall i. \qquad (7)$$

$$Z(i) = max(y_i^1, y_i^2, ..., y_i^N), \forall i. \qquad (8)$$

$$Z(i) = argmax(y_i^1, y_i^2, ..., y_i^N), \forall i. \qquad (9)$$

where y_i^n represent the i^{th} measurement of classifier C_n .

5 CONCLUSIONS

We have investigated in this work the efficiency of different types of features and combination of classifiers for visual emotion recognition in realistic images. Experiments on IAPS dataset have brought to the fore that texture features as well as harmony and dynamism features carry important information for the emotional semantics classification purpose. Moreover, the proposed fusion approach based on the Theory of Evidence has achieved an encouraging classification rate, certainly due to its ability to represent uncertainty and ambiguity of emotions.

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REFERENCES

A. W. M Smeulders, Marcel Worring, S. S. A. G. R. J. (2000). Content-based image retrieval: the end of the early years. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(12):1349–1380.

C. Columbo, A. Del Bimbo, P. P. (1999). Semantics in visual information retrieval. *IEEE Multimedia*, 6(3):38–53.

C.-H. Chan, G.-J.-F. J. (2005). Affect-based indexing and retrieval of films. *ACM Multimedia*, pages 427–430.

C.-T. Li, M.-K. S. (2007). Emotion-based impressionism slideshow with automatic music accompaniment. *ACM Multimedia*, pages 839–842.

Dempster, A. P. (1968). A generalization of bayesian inference. *Journal of the Royal Statistical Society, Series B*, 30:205–247.

Itten, J. (1961). The art of color. *Otto Maier Verlab, Ravensburg, Germany*.

J. Z.Wang, J. L. (2001). Simplicity: Semantics-sensitive integrated matching for picture libraries. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 23(9):947C963.

K. Kuroda, M. H. (2002). An image retrieval system by impression words and specific object names iris. *euro computing*, 43:259–276.

P. Dunker, S. Nowak, A. B. C. L. (2009). Content-based mood classification for photos and music. *ACM MIR*, pages 97–104.

P. J. Lang, M. M. Bradley, B. N. C. (1999). The iaps: Technical manual and affective ratings. *Tech. Rep. GCR in Psychophysiology*.

Picard, R. W. (1997). Affective computing. *MIT Press, Cambridge*.

Q. Wu, C. Zhou, C. W. (2005). Content-based affective image classification and retrieval using support vector machines. *ACII*, pages 239–257.

R. Datta, J. Li, J. Z. W. (2005). Content-based image retrieval: approaches and trends of the new age. *ACM Workshop MIR, Singapore*, pages Nov. 11–12.

Robert Snelick, Umut Uludag, A. M. M. I. A. J. (2005). A survey of affect recognition methods: audio, visual and spontaneous expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 27(3):450–455.

S. Wang, X. W. (2005). Emotion semantics image retrieval: a brief overview. *ACII*, pages 490–497.

Shafer, G. (1976). A mathematical theory of evidence. *Princeton University Press*.

Smets, P. (1990). The combination of evidence in the transferable belief model. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 12(5):447–458.

V.Yanulevskaya, J.C.Van Gemert, e. a. (2008). Emotional valence categorization using holistic image features. *ICIP*, pages 101–104.

W. Wang, Q. H. (2008). A survey on emotional semantic image retrieval. *ICIP*, pages 117–120.

W. Wei-ning, Y. Ying-lin, J. S.-m. (2006). Image retrieval by emotional semantics: A study of emotional space and feature extraction. *IEEE ICSMC*, 4.

Z. Zeng, M. Pantic, G. I. R. T. S. H. (2009). A survey of affect recognition methods: audio, visual and spontaneous expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(1):39–58.