INFORMATION FUSION TECHNIQUES FOR AUTOMATIC IMAGE ANNOTATION

Filippo Vella
Department of Computer Engineering, Università di Palermo, Viale delle Scienze Ed6, Palermo, Italy

Chin-Hui Lee
School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, USA

Keywords: Automatic Image Annotation, Visual Terms, Visual Dictionaries, Multi-Topic Categorization, Maximal Figure of Merit, Information Fusion.

Abstract: Many recent techniques in Automatic Image Annotation use a description of image content based on visual symbolic elements associating textual labels through symbolic connection techniques. These symbolic visual elements, called visual terms, are obtained by a tokenization process starting from the values of features extracted from the training images data set. An interesting issue for this approach is to exploit, through information fusion, the representations with visual terms derived by different image features. We show techniques for the integration of visual information from different image features and compare the results achieved by them.

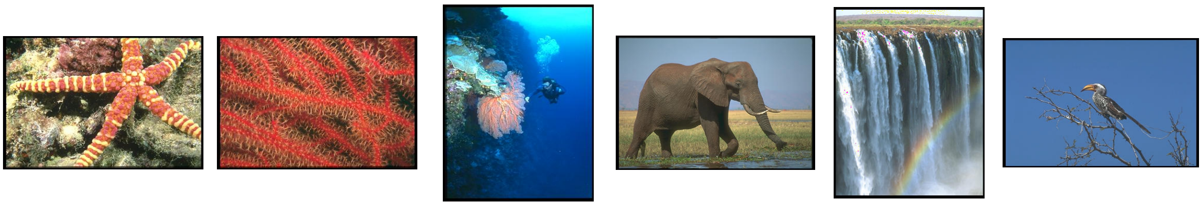
1 INTRODUCTION

Automatic image annotation (AIA) is a process of associating a test image with a set of text labels regarding image content. Different techniques and models have been proposed for AIA aiming at binding visual information in terms of contents with verbal information contained in these labels. Many statistical models have been used to characterize the joint distribution of the keywords and the visual features in a picture. Some recent ones are: Translation Model (TM) (Duygulu et al., 2002), Cross Media Relevant Model (CMRM) (Jeon et al., 2003), Maximum Entropy (ME) (Jeon and Manmatha, 2004), Markov Random Field (MRF) (Carbonetto et al., 2004), Multiple Bernoulli Relevance Model (MBRM) (Feng et al., 2004), Conditional Random Field (CRF)(He et al., 2004) . AIA can be a useful tool to annotate many available images so that concept based image retrieval, as opposed to content based image retrieval, can be performed.

In this paper we consider the connection among image and labels at a coarse level with a set of 50 classes used to divide the images into different categories and bind the class labels to the images visual content. We adopt the AIA techniques used in (Gao et al., 2006) and conduct an experimental study about the use of multiple sets of image features and how they can be combined to perform image classification and annotation.

We consider low level features, such as color and texture, and perform feature extraction on regular 16x16-pixel image grids. These feature vectors are then used to build multiple codebooks, each forming a visual dictionary so that each image can be tokenized into arrays of symbols, one for each visual codebook. By grouping neighboring symbols to form visual sequences of terms, similar to sentences in text, each image can then be represented by a vector with each element characterizing a co-occurrence statistic of the visual terms in a visual document. So each image can be converted into a vector in a similar way to what's done in vector based information retrieval (Salton, 1971). Now image classification can be cast as a text categorization problem (Sebastiani, 2002) in which a topic, or class label, is assigned to a test image according to its closeness to some image class model.

Vella F. and Lee C. (2007).
INFORMATION FUSION TECHNIQUES FOR AUTOMATIC IMAGE ANNOTATION.
In *Proceedings of the Second International Conference on Computer Vision Theory and Applications - IU/MTSV*, pages 60-67



Underwater Reefs | Underwater Reefs | Underwater Reefs | Zimbabwe | Zimbabwe | Zimbabwe

Figure 1: Image samples and their labels.

The used approach (Gao et al., 2004) operates annotation through a Linear Discriminant Function Classifier (LDF) able to associate the visual input to its labels. The LDF is composed by a set of classification units (named LDU or *g*-units), in number equal to the target labels, that are trained to discriminate the positive from the negative examples for a specific label. Each *g*-unit associates to the input image a label referred score.

In this study a LDF classifier is instatiated for each visual dictionary (one for each image feature) and is trained with the dataset samples coded in term of the corresponding visual terms (e.g. Lab histograms, YUV histograms, Gabor Wavelets,…). The scores produced by the *g*-units of different LDF are used as representation of the input images and given as input to information fusion techniques able to merge information derived from the different image features. A comparation of the fusion techniques results is done.

The remainder of the paper is organized as follow: Section 2 discusses the vector representation of images, Section 3 describes the multi-topic classifier and its training process, Section 3 describes the fusion information techniques. Section 5 shows the results of the experiments and in Section 6 are drawn the conclusions.

2 VECTOR BASED IMAGE REPRESENTATION

Image content is typically very rich. Information captured in a generic picture has a number of multiple components that human visual system is able to filter to catch the noticeable elements in a scene. It is not possible to select a fixed set of visual characteristics conveying the main content of symbolic information and it is agreeable that the selection of the minimal set of characteristic, able to describe the visual semantic information, is a hard task. Notwithstanding it is commonly accepted that all the characteristics relevant for the image annotation can be gathered in three main families of characteristics referred to color, texture and shape information.

2.1 Feature Symbolic Level

A visual feature, belonging to one of the above families, describes the image content with a sequence of values that can be interpreted as the projection of the image in the feature space.

The distribution of the feature values in feature space is not random but tends to have different density in the vector space. The centroids of the regions, shaped by the feature vector density, are considered as forming a base for the data representation and any image can be represented as function of these points called *visual terms*.

Visual terms can be used to map single feature values, using in this case a representation simply based on unigrams, or they can be used considering structured displacement of the values. For instance, using the two image dimensions as freedom degrees, powerful structured forms such as spatial bigrams or even more complex structures can be exploited.

The data-driven approach for the extraction of visual terms allows the visual terms to emerge from the data set and build generic sets of symbols with representation power that is limited only by the coverage of the training set.

Although k-means algorithm has been widely used in automatic image annotation (Duygulu et al., 2002)(Barnard et al., 2003), in this work the extraction of the visual terms has been achieved applying the Vector Quantization to the entire set of the characteristic vectors. In particular the codebooks are produced by the LBG algorithm (Linde et al., 1980) ensuring less computational cost and a limited quantization error.

2.2 Image Representation

A single feature allows capturing particular information of the image dataset according to its characteristics. Feature statistics in the image are dependent from the feature itself and are function of its statistical occurrence in the image.

For example, if $A=\{A_1,A_2,\ldots,A_M\}$ is the set of M visual terms for the feature A, each image is represented by a vector $V=(v_1, v_2,\ldots, v_M)$ where the i-th component takes into account the statistic of the term A_i in the image.

Furthermore, the representation of the visual content can be enriched exploiting the spatial displacement of the visual terms in the images.

In Figure 2 is shown the usage of bigrams for an image partitioned with a regular grid. Each element is represented with a visual term identified as *Xij*.

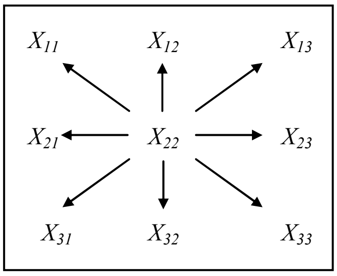


Figure 2: Example of spatially displaced bigrams.

All the couples $X_{22}X_{12}$, $X_{22}X_{13},\ldots,$ $X_{22}X_{11}$ allow a representation of the visual element as bound not only to its own characteristics but also of the nearest image parts.

The increased expressivity of the bigrams allows over performing the results achieved with the unigrams although at the cost of higher dimensionality for image representation.

As example for bigram-based representation, considering a codebook for a single feature formed by M elements, the image representation can be built placing in a vector the unigram-based representation followed by the bigrams-based representation. The total dimension of the vector in this case will be, $M*M+M$. For a codebook of 64 elements the total dimension of the representation is 4160, for 128 elements it is 16512 and so on…

To enhance the indexing power of each element of the representation, a function of the normalized entropy (both for unigrams and bigrams) is computed and used to replace the simple occurrence count. Its value is evaluated as:

$$v_i^j = (1-\varepsilon_i)\cdot c_i^j \big/ n^j \tag{1}$$

where c_i^j is the number of times the element A_i occurred in the j-th image , n_j is the total number of the visual terms in the j-th image . The term ε_i is the normalized entropy of A_i as defined from Bellegarda (2000):

$$\varepsilon_i = -\frac{1}{\log Ns}\sum_{j=1}^{Ns}\frac{c_i^j}{t_i}\log\frac{c_i^j}{t_i} \tag{2}$$

where Ns is the total number of the images, and t_i is the total number the visual term A_i annotates an image in the dataset. The normalized entropy is low if the value has a great indexing power in the entire data set while tends to 1 if its statistic has reduced indexing properties.

Obviously the complexity of the visual information is captured more reliably if more characteristics, as orthogonal as possible, are used together. A straight way to integrate information coming from heterogeneous features is to consider a unique composite vector, formed as juxtaposition of the values of all the features, and extract a unique visual vocabulary from it. This solution, although is largely used, has some drawbacks. In particular, the computational cost of extracting a base for vectors (with k-means or analogue algorithms) is higher if computation is done on a vector as long as the sum of all the features dimensions instead of applying the same algorithm to the single feature vectors. As second drawback, each time a new feature is added to the previous ones, it is necessary to run from scratch the visual term extraction and the tokenization process.

For these reasons is more interesting the study of the usage of already formed codebooks coming from different features that are put together at the symbolic level. In section 4 are shown fusion techniques merging information coming from different features and exploiting different visual dictionaries.

3 AUTOMATIC IMAGE ANNOTATION

The Automatic Image Annotation process is based on a training image set T:

$$T = \{(X, Y) \mid X \in R^D, Y \subset C\} \tag{3}$$

where *(X,Y)* is a training sample. *X* is a *D*-dimensional vector of values extracted as described in Section 2 and *Y* is the manually assigned annotation with multiple keywords or concepts. The predefined keyword set is denoted as

$$C=\{C_j, 1 \leq j \leq N\} \tag{4}$$

with *N* the total number of keywords and *Cj* the *j*-th keyword.

The LDF classifier, used for the annotation, in this paper, is composed by a set of function $g_j(X, \Lambda_j)$ large as the number of the data classes. Each function g_j is characterized by a set of parameters Λ_j that are trained in order to discriminate the positive samples from the negative samples of the *j*-th class.

In the classification stage, each *g*-unit produces a score relative to its own class and the final keyword, assigned the input image *X*, is chosen according to the following multiple-label decision rule:

$$C(X) = \arg\max_{1\leq j\leq N} g_j(X, \Lambda_j) \tag{5}$$

Each *g*-unit competes with all the other units to assign its own label to the input image *X*. The ones achieving the best score are the most trustable to assign the label.

In the annotation case the most active categories are chosen as output of the system and the labels can be chosen applying a threshold to the scores of the

$$C_j(X)= \begin{cases} 1 \; if \; g_j(X,\Lambda_j) > th \\ 0 \; else \end{cases} \tag{6}$$

g-units as in equation (6) or assigning the n-best values labels to the input image.

3.1 Multi-Class Maximal Figure of Merit Learning

In Multi-Class Maximal Figure of Merit (MC MFoM) learning, the parameter set Λ for each class

$$\Lambda = \{\Lambda_j, 1 \leq j \leq N\} \tag{7}$$

is estimated by optimizing a metric-oriented objective function. The continuous and differentiable objective function, embedding the model parameters, is designed to approximate a chosen performance metric (e.g. precision, recall, *F1*).

To complete the definition of the objective function, a one dimensional class misclassification function, $d_j(X,\Lambda)$ is defined to have a smoother decision rule:

$$d_j(X;\Lambda) = -g_j(X,\Lambda) + g_j^-(X,\Lambda^-) \tag{8}$$

where $g_j^-(X,\Lambda^-)$ is the global score of the competing *g*-units that is defined as:

$$g_j^-(X,\Lambda^-) = \log\left[\frac{1}{|C_j^-|}\sum_{i\in C_j^-}\exp(g_i(X;\Lambda_i))^\eta\right]^{\prime} \tag{9}$$

If a sample of the *j*-th class is presented as input, $d_j(X,\Lambda_j)$ is negative if the correct decision is taken, in the other case, the positive value is assumed when a wrong decision occurs. Since eq. (8) produces results from -∞ to +∞, a class loss function l_j is defined in eq. (10) having a range running from 0 to +1:

$$l_j(X;\Lambda) = \frac{1}{1+e^{-\alpha(d_j(X;\Lambda)+\beta)}} \tag{10}$$

where α is a positive constant that controls the size of the learning window and the learning rate, and β is a constant measuring the offset of $d_j(X,\Lambda)$ from 0. The both values are empirically determined. The value of Eq. (10) simulates the error count made by the *j*-the image model for a given sample *X*.

With the above definitions, most commonly used metrics, e.g. precision, recall and *F1*, are approximated over training set *T* and can be defined in terms of l_j function. In the experiments the Det Error that is function of both false negative and false positive error rates has been considered. It is defined as:

$$DetE = \sum_{1\leq j\leq N}\frac{FP_j + FN_j}{2\cdot N} \tag{11}$$

The Det Error is minimized using a generalized probabilistic descent algorithm (Gao et al., 2004) applied to all the linear discriminant *g*-units that are characterized by a function shown in eq. (12).

$$g_j(X,\Lambda_j) = W_j \cdot X + b_j \tag{12}$$

the W_j and b_j parameters form the *j*-th concept model.

4 INFORMATION FUSION IN AIA

The possibility to extract multiple features from image data set makes possible building different visual dictionaries and uses them to represent image content. The integration of the information conveyed with different visual terms is not straight, due to the heterogeneous nature of the different domains, and needs the employment of a strategy.

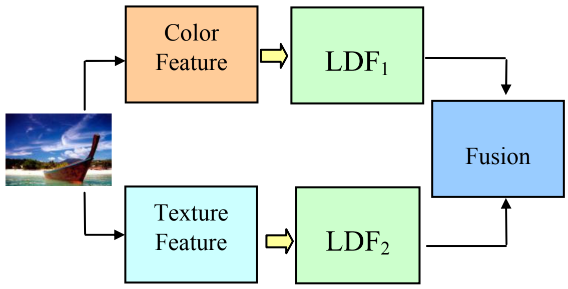


Figure 3: Information fusion from different feature types.

Below are presented fusion information strategies to overcome this gap.

For each different visual dictionary, a LDF classifier is trained using as input the image set coded according to the relative visual terms. When a new image is presented to the system each classifier produces the N dimensional output whose values are the scores produced by the *g*-units. The input image can be therefore represented by *P* *N*-dimensional vectors, where *P* is the number of available visual dictionaries and *N* the number of the labels.

This representation is used as input for the information fusion techniques. We have considered three techniques able to merge the *g*-scores information and have compared the results achieved by them. The techniques are:

a) C5 Decision Tree
b) Weighted Sum of *g*-scores
c) Higher Level Linear Discriminant Function

C5 Decision Tree
The set of all the *g*-units values for the entire training set has been used to build a decision tree according the ID3 algorithm (Mitchell, 1997). In particular, the C5.0/See software has been used (Quinlan, 2006). Each node discriminates the input values according one attribute of the input (in this case the score of a specific *g*-unit) and redirects the elaboration to one or another branch according to the score value. The tree is built placing the nodes accordingly to information theory criteria such as the “information gain” that is strictly related to information entropy of the training data. The leaves allow to associate a label to the input image.

Weighted sum of *g*-scores
The value of each *g*-unit, contained in a LDF classifier, represents the score of each category according to the particular LDF visual feature. Considering to have *P* visual dictionaries, and therefore *P* LDFs, the same number of *g*-scores for each label is available. These values are summed together, with a weight, to have a score dealing with all the visual dictionaries.

$$g_j^*(X,\Lambda_j^*) = \sum_{1\le i\le P} \varphi_{i,j}(X,\Lambda_j^i) g_j(X,\Lambda_j^i) \qquad (13)$$

In the Equation (13) is shown the generic label score achieved with all the *P* different visual dictionaries. The *g** scores are used to select the output labels with equations analogue to equation (5) and equation (6). If the weights φ are set to an equal fixed value each feature gives the same contribution to the global score.

Higher level Linear Discriminant Function
The scores of the *g*-units, equal in number to the number of labels for the number of LDFs for each input images, are used to train a higher level LDF classifier that summarizes the lower LDF outputs.

The output of the higher level LDF (HL LDF) will be the function of the units trained with this new training set. The underlying hypothesis is that the representation achieved in the space of the scores allows a hyperplane to better discriminate the single categories.

In the case we consider to characterize images with two features, for example one for color and the other for texture, each image is therefore represented as 2**N* values, where *N* is the number of labels. The output will be function of the g-units according to functions analogue to equation (5) and equation (6).

5 EXPERIMENTAL RESULTS

The data set used for the experiments is composed by 5000 images in JPEG format divided in 50 classes. The training set has been formed with 4500 images while the remaining 500 images have been used for the test set.

Images are partitioned with a grid of blocks 16x16 pixels. The regular partitioning, although less able to adapt to data, allows characterizing visual input in a regular way independently by the robustness of the segmentation algorithm. The same solution has been adopted by Mori et al. (1999) and Jeon et al. (2004).

The test and training images have been characterized with color and texture features. The color information is represented evaluating RGB histograms of the image blocks. The texture information is represented associating to each block its Gabor Filter Energy histograms.

For all the images of the training set the color and texture features have been computed. The set of the values through the LBG algorithm have been used to form the visual dictionary (one for each feature). The number of visual terms (equal to the size of the codebook) has been fixed to 128. The images have been coded considering the statistics, in all the blocks, in terms of unigrams and bigrams with vectors composed by 16512 elements. For each visual dictionary a LDF has been trained setting the parameter η in equation (9) equal to 5.

The experiments have been done considering a variable set of classes and in particular with 5, 20 and 50 classes to test the fusion information techniques when input values spreading is increased.

The *g*-scores, produced by the trained LDFs (the first for the color feature and the second for the texture feature), have been used as input for the fusion information step.

The C5 decision tree has been created with the See5/C5.0 software (Quinlan, 2006) with all the default parameters and setting the pruning parameter to the 25%. The performance of the information fusion has been evaluated considering a single label assigned to the input image in terms of Det Error. The results for the decision trees are shown in Table 1.

Table 1: Det Error for the training and test error.

	Train Set Error N=5	Test Set Error N=5	Train Set Error N=20	Test Set Error N=20	Train Set Error N=50	Test Set Error N=50
Color	0.63	7,67	8.82	31.17	14.72	36.12
Texture	0.63	11.77	10.29	35.14	19.39	42.85
DT (c5)	0.00	7.52	2.26	38.62	9.42	41.94
Weighted Sum	0.00	3.80	5.87	31.78	11.70	38.26
HL LDF	0.00	3.80	7.25	33.08	22.70	38.57

Regarding the decision tree, the results in table show that in the cases the number of classes is 5, the decision trees perform better that the LDFs trained with single feature values. When the number of classes is increased, the performance tends to be an average of the single feature LDFs performance. Furthermore a big difference, in terms of Det Error, is produced between train and test images set. This difference can be attributed to the limited generalization capability of the decision tree.

Table 1 shows also that the other fusion techniques perform better than decision trees and typically over perform the results achieved by the single feature LDFs.

The results of these fusion methods, as the weighted sum of the *g*-scores and the HL LDF are compared, in the above figures, through the precision and recall analysis. The variation of the threshold in the annotation process (Equation(6)) affects the number of retrieved images. With higher values of the threshold, fewer labels are retrieved and so the recall (that is the number of relevant retrieved images above the number of relevant images) is low while the precision (the number of relevant retrieved images above the number of relevant images) is typically high.

With lower values of the threshold more samples are retrieved, the recall is increased but the precision is necessarily diminished. This kind of analysis is often used in document retrieval but also in image retrieval field it has proven useful for performance appraisal (Landgrebe et al., 2006).

The plotting for 5, 20 and 50 classes of precision versus recall are shown in the Figure 4, Figure 5 and Figure 6.

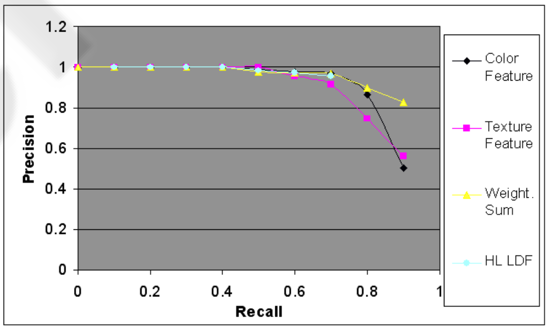


Figure 4: Precision versus recall for image data set of 5 Classes.

In Figure 4 is shown the plot of the precision versus the recall for the described fusion techniques compared to the performance achieved by the single features (RGB histograms and Gabor energy histograms) when the number of classes is set to 5.

The weighted sum of the single scores produces the best performance among the fusion techniques and improves the performance of the single feature annotation too.

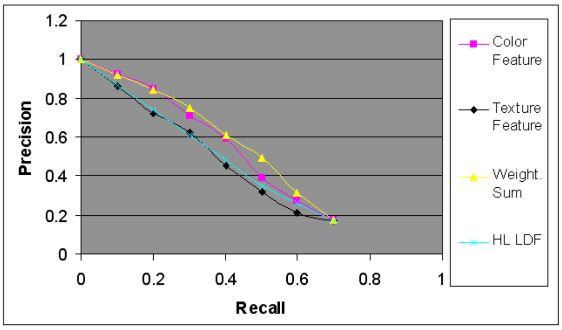


Figure 5: Precision versus recall for image data set of 20 Classes.

When the number of classes is 20 (Figure 5), the fusion technique using the weighted sum of the *g*-scores performs better than the other techniques and the results of single features are over performed.

The fusion with the LDF in cascade to the single feature LDF (HL LDF) achieves results that are intermediate between the performances based on single features. The results are, for the same value of recall, less precise than in the 5 classes experiments.

This behaviour can be attributed to the fact that the scores given by the single features LDF produce a less evident discrimination among class. Notwithstanding, the weighted sum of the scored still allows a good discrimination.

Finally, the performance for 50 classes is shown in Figure 6. In this case both the fusion techniques of weighted sum and LDF achieve results that are the between the performance of the single feature LDFs.

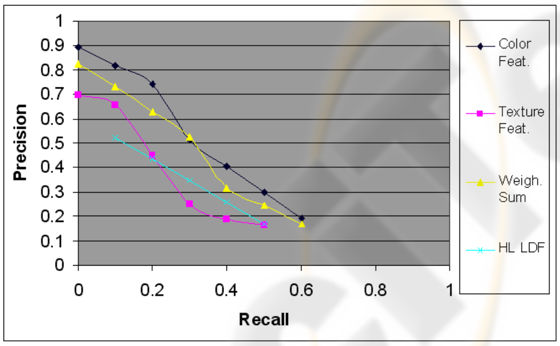


Figure 6: Precision vs Recall for the fusion techniques applied to the Automatic Annotation of 50 Classes.

The annotation results, achieved with LDF trained with color features, for the most of values of the recall parameter, produce better results than the other fusion techniques. In this case, due to the increased scattering of the feature values, the representation in the feature space does not allow a clear interclass separation and fusion techniques cannot exploit the multiple features representation.

In Table 2 are shown the False Positive Rate and False Negative Rate achieved for the input set formed by 5, 20 and 50 classes when five labels are associated to each image.

Table 2: False Positive and False Negative rates for the fusion techniques when 5 labels are assigned to the input images.

	5 Classes		20 Classes		50 Classes	
	FP	FN	FP	FN	FP	FN
Color	0.00	0.00	1.31	22.86	0.65	31.80
Texture	0.00	0.00	1.87	27.38	1.00	49.04
Weight. Sum	0.00	0.00	1.38	21.79	0.75	36.60
HL LDF	0.00	0.00	1.16	22.94	0.82	40.40

Due to the definition for False Positive (number of wrongly annotated images above the number of negative samples) and False Negative error rates (number of wrongly not annotated images above the number of positive samples), their value in the multi-class case can be very different as the table shows. The reason is mainly due to different values of the value of negative samples (denominator of False Positive Rate) and the number of positive samples (denominator of False Negative Rate). For example, for 50 classes the number of positive sample, in the test set, for each label is 10 set while the number of negative samples is 490. The error rates are accordingly affected.

The results in Table 2 confirm the results of the precision-recall analysis also when multiple labels are associated to the images. The weighted sum of the *g*-scores achieves the best results among the fusion techniques, while the number of input classes is 20 or less it over performs the results achieved by the single feature LDF. When the number of classes is increased the color feature LDF achieves better results while the fusion techniques produce results between the results of the single feature LDFs.

The values of the errors show that the annotation with this technique can be reliably performed when the labels are well represented by the LDF scores and it typically happens when the spreading of the visual terms in the training set is limited. When the inter-class value spreading is excessive (increasing number of classes) other models should be applied for the single feature representation.

In the below table are compared precision and recall of the fusion technique adopting the weighted sum of the *g*-score for the classification of fifty classes with the published results of the state of art annotation techniques. The proposed technique show a good improvement although must be said that a straight comparison is impossible due to the different adopted features and the number of classes.

Table 3: Comparision of proposed technique with state of art annotation techniques.

	TM	CMRM	ME	MBRM	Proposed Tech.
Prec	0.06	0.10	0.09	0.24	0.36
Recall	0.04	0.09	0.12	0.25	0.36

6 CONCLUSION AND FUTURE WORKS

Image annotation needs to exploit information from different orthogonal features to capture the visual elements carrying a symbolic meaning matched with the text labels.

The shown techniques use information from different features and merge together visual information represented in term of scores related to different labels. Different information fusion techniques have been compared showing that, for this application, the weighted sum of *g*-scores produces better results than other fusion techniques.

The information fusion produced putting a HL LDF to summarize the results of the first stage LDFs, allows an improvement in performance when the characterization of input images, through g-units scores, is adherent to their content. Decision trees have a reduced utility in this case mainly due to the reduced generalization capability.

Further investigations will be focused on the training of the images in terms of more specific classes or sub-classes that despite a reduced number of samples for each category are more specific as content. The application of more complex models instead of LDF can also allow capturing the positive and negative classes in a more flexible way and allow a better performance for fusion algorithms.

ACKNOLEDGEMENTS

Authors would like to thank Kobus Barnard and Shen Gao for their help with the images data set and Rulequest company for the evaluation version of the See5/C5.0 software for decision trees building.

REFERENCES

Barnard K., Duygulu P., Forsyth D., de Freitas N., Blei D., Jordan. M., 2003, “Matching words and pictures”, *Journal of Machine Learning Research*, Vol.3, pp 1107-1135.

Bellegarda J.-R., 2000, “Exploiting latent semantic information in statistical language modelling”, *Proc. of the IEEE*, Vol. 88, No. 8, pp 1279-1296.

Blei D., Jordan M.-I., 2003, “Modeling annotated data”, *ACM SIGIR*.

Carbonetto P., de Freitas N., Barnard K., 2004, “A statistical model for general contextual object recognition”, *Proc. of ECCV*.

Duygulu P., de Freitas N., Barnard K., Forsyth D., 2002, “Object recognition as machine translation: Learning a lexicon for a fixed vocabulary”, *Proc. of ECCV*.

Feng S.-L., Manmatha R., Lavrenko V., 2004, “Multiple Bernoulli relevance models for image and video annotation,” *, Proc of CVPR’04*.

Gao S., Wang D.-H., Lee C.-H., 2006, “Automatic Image Annotation through Multi-Topic Text Categorization”, *Proc. of ICASSP*.

Gao S., Wu W., Lee C.-H., Chua T.-S. , 2004, “A MFoM learning approach to robust multiclass multi-label text categorization”, *Proc. of ICML*.

He X.-M., Zemel R. S., Carreira-Perpiñán M. A., 2004, “Multiscale conditional random fields for automatic image annotation”, *Proc. of CVPR*

Jeon J., Manmatha R., 2004., “Using maximum entropy for automatic image annotation”, *Proc of ICVR*.

Jeon J., Manmatha R., 2003, “Automatic image annotation and retrieval using cross-media relevance models”, ACM SIGIR.

Landgrebe T.C.W., Paclik P., Duin R.P.W., Bradley A.P., 2006, "Precision-recall operating characteristic (P-ROC) curves in imprecise environments", *Proc. of the 18th Int. Conf. on Pattern Recognition*

Linde Y., Buzo A., Gray R., 1980. “An Algorithm for Vector Quantizer Design”. *IEEE Transaction on Communications*, vol. 28 (1), pp 84–94.

Mitchell T.M., 1997, *Machine Learning*, McGrawHill

Mori Y, Takahashi H., Oka R., 1999, Image-to-word transformation based on dividing and vector quantizing images with words, In *Proc of MISRM'99*

Quinlan J.R., 2006, Data Mining Tools See5 and C5.0, from Rule Quest web site: www.rulequest.com/ see5-info.html

Salton G., 1971, *The SMART Retrieval System*, Prentice-Hall, Englewood Cliffs, NJ

Sebastiani F., 2002, “Machine Learning in Automated Text Categorization”, ACM Computer Surveys, Vol. 34, No. 1, pp 1-47.

Wang D.-H, Gao S., Tian Q., Sung W.-K, 2005, “Discriminative fusion approach for automatic image annotation”, *Proc. of IEEE 7th Workshop on Multimedia Signal Processing*