Information Fusion in Multimedia Information Retrieval

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Abstract. In retrieval, indexing and classification of multimedia data an efficient information fusion of the different modalities is essential for the system's overall performance. Since information fusion, its influence factors and performance improvement boundaries have been lively discussed in the last years in different research communities, we will review their latest findings. They most importantly point out that exploiting the feature's and modality's dependencies will yield to maximal performance. In data analysis and fusion tests with annotated image collections this is undermined.

1 Introduction

The multi modal nature of multimedia data creates an essential need for information fusion for its analysis, indexing and retrieval. Fusion has also great impact on other tasks like object recognition, since all objects exist in multi modal spaces. Information fusion has established itself as an independent research area over the last decades, but a general formal theoretical framework to describe information fusion systems is still missing [14]. One reason for this is the vast number of disparate research areas that utilize and describe some form of information fusion in their context of theory. For example, the concept of data or feature fusion, which forms together with classifier and decision fusion the three main divisions of fusion levels, initially occurred in multi-sensor processing. By now several other research fields found its application useful. Besides the more classical data fusion approaches in robotics, image processing and pattern recognition, the information retrieval community discovered some years ago its power in combining multiple information sources [23].

The roots of classifier and decision fusion can be found in the neural network literature, where the idea of combining neural network outputs was published as early as 1965 [10]. Later its application expanded into other fields like econometrics as forecast combining, machine learning as evidence combination and also information retrieval in e.g. page rank aggregation [23].

In opposite to the early application areas of data, classifier and decision fusion, researchers were for a long time unclear about which level of information fusion is to be preferred and more general, how to design an optimal information

fusion strategy for multimedia processing systems. This can be seen in recently published approaches that solve similar tasks and nevertheless use different information fusion levels. Examples using classifier fusion are multimedia retrieval [28], multi-modal object recognition [12], multibiometrics [15] and video retrieval [29]. Concerning data fusion, the applications that can be named are multimedia summarization [1], text and image categorization [7], multi-modal image retrieval [27] and web document retrieval [19]. Other problems of interest are the determination of fusion performance improvement compared to single source systems and the investigation of its suspected influence factors like dependency and accuracy of classifiers and data.

Compared to other application fields of information fusion, there is in multimedia a limited understanding of the relations between basic features and abstract content description [26]. Many scientists have approached this problem in the past empirically and also attempted to justify their findings in theoretical frameworks. Lately the information fusion community did important progress in fusion theory that have not yet been considered for multimedia retrieval tasks. In this paper we give first (Section 2) a review on information fusion in a generic context and what is important in practice for fusion system design. Especially it will be pointed out that there is more to consider than the level of fusion. The section includes a discussion on influence factors of fusion effectiveness and the design of an optimal fusion system. In section 3, the task of semantic classification of keyword annotated images is analyzed in order to suggest an appropriate fusion strategy in accordance with the latest findings in information fusion. The paper also confirms this with experimental results.

2   General Overview on Information Fusion

The JDL working group defined information fusion as "an information process that associates, correlates and combines data and information from single or multiple sensors or sources to achieve refined estimates of parameters, characteristics, events and behaviors" [13]. Several classification schemes for information fusion systems have been proposed in literature, whereby the one from the JDL group is probably the most established. This functional model represents components of a fusion system in 4 core levels of fusion (L0-L3) and 2 extension levels (L4,L5). Here L0-L3 are the data or feature association and there above the object, situation, and impact refinement. The extension levels (L4, L5) consist of the process and the user refinement.

The connection between inferencing and information fusion, which is utilizable for automation of the information fusion system design, is presented in [13]. The first step is the discovery of patterns and meaningful relationships in the data through abductive, innovative reasoning. This is best approached by data mining and hence data association techniques. The discovered patterns are afterwards generalized and validated in models by applying inductive generalization. The model parameters are estimated via a set of training data during situation refinement. The last step, which uses deduction, is the application of the model

or template to real-time raw data in order to detect evidences for patters similar to those the model was trained with.

In [2], an overview of information fusion scenari in the context of multi modal biometrics is given, which can be easily adapted to general tasks. Hence in information fusion the settings that are possible are: (1) single modality and multiple sensors, (2) single modality and multiple features, (3) single modality and multiple classifiers and (4) multi modalities. Where in the latter case for each modality one of the combinations (1)-(3) can be applied. The multi modal fusion can be done serial, parallel or hierarchical. For completeness reasons, we add a scenario found in [15]: single modality and multiple sample, which is of importance in information retrieval approaches like bagging.

The gain of information fusion is differentiated in [14]: "By combining low level features it is possible to achieve a more abstract or a more precise representation of the world". This difference in the fusion goal is also covered in the Durrant-Whyte classification of information fusion strategies [13], which refers to complementary, cooperative and competitive fusion. In the first case, the information gain results from combining multiple complementary information sources to generate a more complete representation of the world. Here, the overall goal is to exploit the sources diversity or complementarity in the fusion process. The latter two cases provide a reduced overall uncertainty and hence also increased robustness in fusion systems by combining multiple information sources or, e.g., multiple features of a single source. These latter strategies utilize the redundancy in information sources. Since the sum of complementarity and redundancy of a source equals a constant, it is only possible to optimize a fusion system in favor of the one or the other [3].

In general the benefit of fusion, presuming a proper fusion method, is that the influence of unreliable sources can be lowered compared to reliable ones [18]. This is of a high practical relevance, because during system design it is often not clear how the different features and modalities will perform in real world environments. By applying information fusion, the dependency on the reliability of information sources can be minimized.

Further aspects of information fusion like the system architecture (distributed, centralized) and utilization of certain mathematical tools (probability and evidence theory, fuzzy set and possibility theory, neural networks, linear combination) can be found in an older review on information fusion [11], but their detailed presentation is out of the scope of this paper.

2.1   Information Fusion System Design

Based on the theory presented in the last section, in the practice of system design, the following points have to be considered: sensors or sources of information, choice of feature sets, fusion level, fusion strategy and fusion architecture and if further background or domain knowledge can be embedded [14].

The choice of sensors and information sources is normally limited by the application. The available sources should be considered in regard to their inhered

noise level, cost of computation, diversity in between the set and its general ability to describe and distinguish the targeted at patterns.

During feature selection, one must realize that feature values of different modalities can encounter a spectrum of different feature types: continuous, discrete and even symbolic. Modality fusion dealing with mixed feature type data is more difficult and complex [30], especially for joint fusion at data level, since a meaningful projection of the data to the result space has to be defined. In the case of only continuous features observed from different modalities, the information fusion is also not trivial, because an appropriate normalization has to be applied [2].

The most common location of fusion are at data/feature, classifier/score level and decision level. Hence, a decision between low level or high level fusion must be taken, but also hybrid algorithms that fuse on several levels are possible. An exception is presented in [25], where the authors fuse kernel matrices. In [14] the authors proved, with the help of their category theory framework, that classifier and decision fusion are just special cases of data fusion. Furthermore they stated that a correct fusion system is always at least as effective as any of its parts, because, due to fusion several sources, more information about the problem is involved. The emphasize is here on 'correct', so inappropriate fusion can lead to a performance decrease. Attention should be payed to the difference between data fusion and data concatenation. The latter is circumventing the data alignment problem and thus is not having the power of data fusion. But it can be an easy and sufficient solution for compatible feature sets.

Many publications so far treated the topic data versus decision fusion by investigating the pros and conc of each fusion type. Data fusion can, due to the data processing inequality, achieve the best performance improvements [17], because at this early stage of processing the most information is available. Complex relations in data can be exploited during fusion, provided that their way of dependence is known. Drawbacks in data and feature fusion are problems due to the 'curse of dimensionality', its computationally expensiveness and that it needs a lot of training data. The opposite is true for decision fusion. It can be said to be throughout faster because each modality is processed independently which is leading to a dimensionality reduction. Decision fusion is however seen as a very rigid solution, because at this level of processing only limited information is left.

The fusion strategy is mostly determined by the considered application. For example, all sensor integration, image processing, multi modal tracking tasks and the like execute cooperative fusion since they exploit temporal or spatial co-occurrence of feature values. However, for information retrieval systems the situation is not as trivial. Three different effects in rank aggregation tasks that can be exploited by fusion were observed by [4]:

(1) Skimming effect: the lists include diverse and relevant items
(2) Chorus effect: the lists contain similar and relevant items
(3) Dark Horse effect: unusually accurate result of one source

According to the theory presented in the last section, it is impossible to exploit all effects within one approach because the required complementary (1) and cooperative (2) strategy are contradictory. Furthermore it is unknown which effect will be contained in the result lists.

The task of multi modal information retrieval and classification, e.g. joint processing of images aligned with texts or annotated with keywords, was approached in the past with success using cooperative strategies like LSI, which uses feature co-occurence matrixes, or mixture models, which exploit the feature joint probability [19]. The same is true for complementary ensemble methods, that train classifiers for each modality separately and fuse them afterwards [5].

2.2 Performance Improvement Boundaries

The lack of a formal theory framework for information fusion caused a vibrant discussion in the last years about the influences on fusion results and especially on theoretical achievable performance improvement boundaries compared to single source systems. Early fusion experiments have shown thorough performance improvement. Later publications accumulated that reported about ambivalent fusion results, mostly, where ensemble classifier were outperformed by the best single classifier. So the information fusion community began to empirically investigate suspected influence factors such as diversity, dependency and accuracy of information sources and classifiers. Based on the experiments explanations for the fusion result ambiguity and mostly application specific upper and lower bounds of performance improvements were found. This section will summarize their findings.

First investigations of these problems were undertaken in competitive fusion on behalf of decorrelated neural network ensembles [20], that outperformed independently trained ones. The overall reduced error is achieved due to negative correlated errors[1] in the neural networks, that average out in combination. [6] confirmed that more diverse classifiers improve the ensemble performance, even if weak classifiers were involved. The bias-variance decomposition of the mean square error of the fusion result serves as theoretical explanation: more training lowers the bias, but gives rise to variance of the fusion result. The bias-variance-covariance relation is an extension of the former decomposition [16], that shows theoretically that dependencies between classifiers increase the generalization error compared to independent ones. So this strategy achieves a more precise expectation value in the result due to averaging over the inputs.

A theoretical study on complementary fusion [15] applied to multibiometrics found its lower bound of performance improvement for highly correlated modalities and the upper bound for independent ones. This strategy works only for truly complementary tasks, which means that it is aimed at independent patterns in the data, as in a rank aggregation problem where the combined lists

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[1] Negative correlated errors are here referred to as being signals with an opposite developing of their values, not that only negative correlation coefficients are found between the signals.

contain a significant number of unique relevant documents [22]. Here, the opposite of the bias-variance decomposition for averaging applies: more training rises the bias (ambiguity) and lowers the variance of the result. But the influence of the classifier's bias, variance and their number, affects the fusion result not as much as dependency [10]. For this fusion strategy high level or late fusion is most efficient, since there are no dependencies that can be exploited at data level.

In practice often independence between the fusion inputs is assumed for simplicity reasons or in reference to the diversity of involved modalities. But this is not true e.g. for modalities in multibiometrics [15] and most certainly also not for modalities of other applications, even though it may contain only small dependencies. Applying in this situations high level fusion will hence never yield the maximum theoretical possible fusion performance improvement, because the information reduction caused by processing makes it impossible to exploit data dependencies completely in late fusion. On the other hand, data level fusion can have blatant disadvantages in practice due to the 'curse-of-dimensionality' [12] and perform badly towards generalization, modeling complexity, computational intensity and need of training data. A solution for the trade off data versus classifier fusion, can be a hybrid system fusing on several levels.

Empirical tests investigating optimal features in an approach to fuse visual clues from different sources, hence cooperative fusion, showed that they should be redundant in their values, but complementary in their errors [8]. In [17] fusion performance is investigated on behalf of a multi modal binary hypothesis testing problem as e.g. used in multibiometrics. Considering the error exponents for the dependence and independence assumption for the modalities, it is found that the dependent case gives the upper performance improvement bound, and the case of independence the lower.

A comparison of a complementary and cooperative classifier fusion applied to multibiometrics [21] gave in a first try an equal high performance improvement compared to the single modality system. Having incorporated a more precise estimate of the modality's dependencies into the cooperative fusion, a further performance improvement was achieved. Admittedly, this gain over the complementary fusion is small, which is due to the little dependencies between the modalities and furthermore, it needs a lot of training data to estimate the correlation matrix. So in practice there is a trade off between performance improvement and computational cost. Often the independence assumption will achieve sufficient results. The authors [21] show as well that class-dependent training of classifiers can help to improve the system's ability to discriminate the classes and hence improve the system's overall performance.

After having reviewed the fundamentals of information fusion, the next section will analyze first the data of a multi modal classification task, specifically of keyword annotated images. Second some simple fusion test undermine the presented information fusion theory and should lead the way to develop an efficient solution to the problem.

3 Data Analysis towards Effective Multimedia Information Retrieval

Due to the high interest in multimedia processing in the past many multi modal collections have been made available to the research communities. Here 2 examples of them are investigated. The Washington database contains 21 image classes of locations like Australia and Italy, but also semantic concepts like football and cherry trees. Most of the images are manually annotated with a few keywords (1-10). Classes that with no annotation were left out in the tests, so we experimented with 16 classes, containing in all 675 images that are nearly equally distributed over the classes. The second collection is a subset of the Corel database, for which [9] created keyword annotations. The final set contains 1159 images in 49 classes, where the images are unequally distributed over the classes that represent similar concepts as in the Washington collection. Another thing to point out is that the annotations also include complete nonsense keyword sets, which makes it similar to what one would expect in real world data. For pre-processing GIFT features [24] (color and texture histograms) for all images and term-frequency vectors for their annotations were computed. Hence each data sample in the Washington collection is described by 624 features (166 color, 120 texture and 338 text) and in the Corel collection by 2035 features (166 color, 120 texture and 1749 text), where the textual features are very sparse.
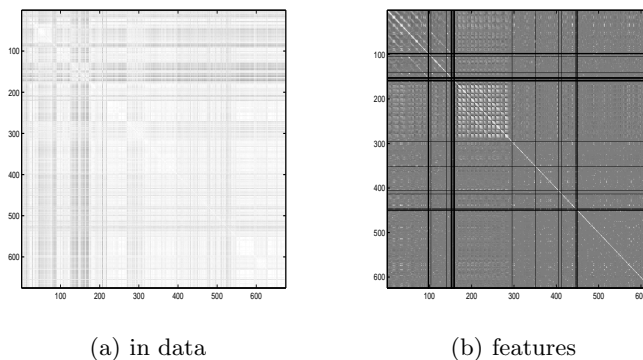

(a) in data　　　　　　　(b) features

Fig. 1. Correlation analysis of Washington collection

The figures 1 and 2 show the correlation matrices over the data and features of the Washington and Corel collection respectively, where bright areas represent high correlation and darker areas lower. The black fields emerge, when the correlation coefficient could not be calculated due to division by zero. The number of significantly correlated data samples is in both collections (Washington: 99%, Corel: 99%) much higher than the significantly correlated feature pairs (Washington: 17%, Corel: 3%). Apparently, the dependencies in the Corel
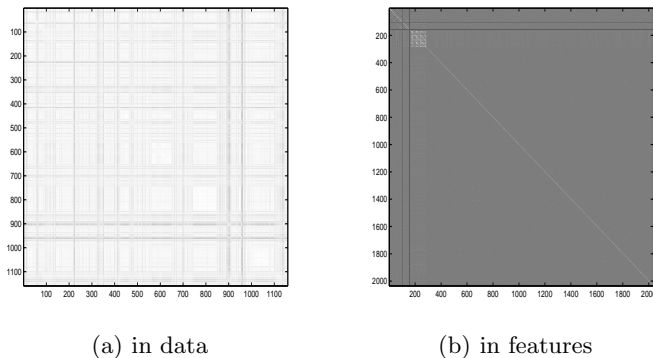
(a) in data   (b) in features

Fig. 2. Correlation analysis of Corel collection

features are much smaller than in the Washington collection. Inter-modal dependencies for both collection are summarized in table 1. The average dependencies turn out to be close to zero, since positive and negative correlation coefficients C are contained. The highest correlation coefficients can be found between the histograms and textual features, where as between color and texture histogram smaller dependencies appear.

Table 1. Inter-modal dependencies of Washington and Corel collection

C	Washington			Corel		
	color-texture	color-text	texture-text	color-texture	color-text	texture-text
av	0.026	0.002	0.0008	0.003	$6.0e-05$	0.001
max	0.542	0.858	0.739	0.435	0.990	0.804
min	-0.396	-0.224	-0.396	-0.258	-0.177	-0.294

The correlation between the extracted features of the Washington and Corel collection should be exploited in order to develop an efficient information fusion system for the classification task.

3.1 Information Fusion Experiments

For the fusion experiments we used a support vector machine (SVM) classifier with rbf kernel as described in [5]. First we compared several simple fusion approaches: (1) hierarchical SVM, which is one SVM classifier for each modality and then as well a SVM classifier to fuse their results, (2) concatenated data and SVM, which uses all modalities concatenated as classifier input, (3) averaging the classifier outputs of the modalities, (4) weighted sum, which is the same as (3), but weights the best modality (text) more than the others and (5) majority vote of the classifier outcomes.

The tests were run as one-against-all classifications without any optimalization of the classifier to the data using 7 positive and 7 negative samples for the Washington collection and 5 positive and 7 negative samples for the Corel collection to train the classifiers. Thereafter their performance is evaluated by applying the classifiers to the remaining data samples. The classification error is given in percent and averaged overall classes of a collection. Additionally the percentage of false alarm (misclassifications in the currently to distinguish class) and miss (misclassifications in the negative class) are used for evaluation.

Table 2. Fusion experiments on Washington collection

in %	color	texture	text	hier SVM	concat SVM	averaging	weigh sum	maj vote
classification error	39.1	46.1	35.9	**13.1**	42.4	40.9	38.6	37.3
false alarm	6.2	28.5	5.6	19.8	10.4	5.7	**3.7**	7.1
miss	40.9	47.1	37.6	**12.7**	44.2	42.9	40.6	39.0

Table 3. Fusion experiments on Corel collection

in %	color	texture	text	hier SVM	concat SVM	averaging	weigh sum	maj vote
classification error	45.3	47.7	45.5	**15.4**	46.9	47.2	46.8	44.8
false alarm	26.5	37.9	20.3	49.5	23.8	44.8	**18.5**	21.8
miss	45.6	47.9	45.9	**14.7**	47.3	47.6	47.3	45.2

The experimental results are given in table 2 (Washington) and 3 (Corel). For both collections the hierarchical fusion performs superior to all other approaches considering the overall classification error, but the classification results in the positive class (false alarm) are throughout better with the simpler fusion strategies. Here, majority vote is best in the overall classification and weighted sum fusion in the false alarm rate. In the overall performance the simple fusion strategies have unsurprisingly trouble to cope with the badly performing classifier results of the modalities. Text and color based classification work better than the texture based one, but in general they achieve only unreliable results especially for the negative class (miss). A side observation made during testing is that the feature dependencies, are in their tendency similar to the correlation between the classifier outputs of the modalities. The correlation between color/texture and text classifier is larger than for the color and texture.

The observed results can be said to be ambiguous between the preference of learning and simple fusion approaches. Because the better performance of the

simple fusion in discriminating the positive classes is in favor of information retrieval, where it would lead to more relevant documents in the result list. But this better performance compared to the learning approach is more than compensated by the performance in distinguishing the negative class. Here, more tests with improved classifier performance of the modalities should show, if this decreases the miss rate. Then simple fusion fusion would be a very interesting approach for large scale problems, because of its low computational complexity.

In the second experiment, we investigated how the usage of independent and dependent features influences the performance. Since we did not want to search for more or less correlated input features, we created feature subsets for each modality with especially correlated or uncorrelated features. In order to do so, we chose features, that have at least once a correlation coefficient with another feature larger than $C > \alpha$ (dependent features) and smaller than $C < \beta$ (independent features) respectively taken as $\alpha = [0.95, 0.75, 0.5]$ and $\beta = [5.0e - 07, 0.05, 0.5]$. The rest of the experiment setup stayed the same as in the first experiment.

Table 4. Fusion of dependent and independent feature subsets on Washington collection

in %	color	texture	text	full	dependent	independent
dependent: $C > 0.95$ (14/166,14/120,147/338)						
independent: $C < 5.0e - 07$ (152/166, 120/120, 330/330)						
classification error	38.2	45.9	33.6	**10.8**	**10.8**	**10.8**
false alarm	8.3	31.7	**2.7**	23.6	59.2	23.6
miss	39.8	46.6	35.3	10.0	**8.7**	10.0
dependent: $C > 0.75$ (58/166,71/120,186/338)						
independent: $C < 0.05$ (152/166, 120/120, 330/330)						
classification error	41.1	47.6	36.1	**12.0**	12.9	**12.0**
false alarm	10.3	27.7	**6.2**	28.7	33.3	28.7
miss	42.8	48.7	37.9	**11.0**	11.9	**11.0**
dependent: $C > 0.5$ (123/166,120/120,253/338)						
independent: $C < 0.5$ (166/166, 120/120, 330/330)						
classification error	41.1	47.5	36.6	11.8	**11.4**	11.8
false alarm	6.5	32.3	**3.2**	17.2	16.5	17.2
miss	42.9	48.4	38.5	11.3	**10.9**	11.3

Table 4 shows the results for the Washington collection, where the number of features selected for each modality (color, texture, text) is given in brackets. The selection of independent features did not reduce the feature set as much as for the dependent feature set. That is why another criterion for creating the subset

has to be found, because with only a slight reduction in the color modality the independent features perform the same as the full set.

The overall performance of the dependent subset is also the same, which is quite surprising since especially in the biggest reduction step only 175 features of 624 were used. But the dimensionality reduction gives rise to the false alarm rate. For weaker selection thresholds more features are selected and hence the performance results approach the results of full feature set.

With this experiment we were able to show for now only that a dimensionality reduction in the input features using correlated subsets is possible with only a little decrease in performance. More extensive tests with e.g. truly differently correlated input features or even artificially created data sets have to be done to prove its general usefulness for performance improvement of information fusion systems.

In the last experiment we changed the feature selection rule to chose the feature subsets not according to the correlation coefficients of the whole collection, but according to the correlation found in the currently to distinguish class. With this dynamic, class-dependent selection the feature subsets should contain those features, that are especially helpful in discriminating this class from the negative samples. The results for the Washington and Corel collection are presented in table 5, where this time the independent feature subset selection reduced the full set significantly.

Table 5. Fusion with class-dependent feature subsets

in %	color	texture	text	full	dependent	independent
Corel dependent: $C > 0.75$, independent: $C < 0.05$						
classification error	47.4	48.4	45.6	**17.1**	24.4	22.9
false alarm	29.8	29.1	**21.8**	45.4	43.5	42.5
miss	47.7	48.8	46.1	**16.6**	24.0	22.6
Washington dependent: $C > 0.75$, independent: $C < 0.05$						
classification error	43.2	48.7	37.6	**11.9**	19.6	17.2
false alarm	6.2	24.8	**3.9**	15.0	22.9	22.1
miss	45.3	50.1	39.5	**11.7**	19.4	16.8

The results for the Corel set show an overall performance loss of the dependent and independent feature subsets compared to the full set, but as well a slight improvement in the false alarm rate. This in fact means that the class-dependently chosen feature subsets are able to distinguish the positive examples better from the negative ones. The same effect is not observed in the experiment with the Washington collection. So further tests are necessary to clarify, if a class-dependent feature selection based in correlation is helpful for better discriminating the classes.

4   Conclusions and future work

In retrieval, indexing and classification of multimedia data an efficient information fusion of the different modalities is essential for the system's overall performance. Since information fusion, its influence factors and performance improvement boundaries have been lively discussed in the last years in different research communities, our summarization of their findings will be helpful for all fusion system designers in future.

We showed that the often represented idea of utilizing independent features or modalities achieves the best information fusion results, is only true for complementary fusion tasks. Those are rare in practice, since even different modalities inhere always some dependencies as our data analysis of visual and textual features of annotated images confirmed. Hence, the best information fusion performance and thereby as well the retrieval, indexing or classification approach's performance will be maximal, if those dependencies are exploited, preferably at data level. In practice, the exploitation of feature or modality dependencies presumes their statistical knowledge, which can be problematic. Other disadvantages can arise in data fusion for large feature sets caused by the 'curs-of-dimensionality'. That is why classifier fusion that can exploit the modalities dependencies and fusion approaches that fuse on several levels seem to be a promising solution.

Another way to achieve better information fusion performance is to utilize class-dependent classifier settings. This helps in discriminating the positive from the negative classes. Our experiments have shown ambiguous results, so clarifying this is one of the topics we will investigate in future. Furthermore, we plan to develop an efficient information fusion approach for multimedia retrieval of images and their aligned text as can be for example found in web pages.

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