Symbol Recognition using a Galois Lattice of Frequent Graphical Patterns

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***Abstract*—Graphics recognition is an important task in many real-life applications. In this article, we propose a new approach to recognize graphical symbols by the use of a frequent Galois lattice. We propose to build a concept lattice not in terms of graphical patterns but in terms of frequent graphical patterns. The purpose of this paper is twofold : first, we try to identify the best primitives from a given graphical symbol based on a descriptor invariant to rotation, translation and scaling. Each symbol is decribed using a feature vector computed on stable neighborhood for a set of points chosen randomly from the symbol. Secondly, we propose a new recognition approach based on a frequent Galois lattice. The obtained concept lattice based on frequent patterns is used as a classifier. The retrieval performance and behavior of the method have been tested for symbol recognition.We have compared our method with others based on different descriptors and classifiers. Our approach proves that the symbol description method and the algorithm used to extract frequent attributes to build the frequent Galois lattice are suitable to the recognition process.**

***Keywords*-Symbol recognition, Descriptor, Graphical symbol, Galois Lattice, Frequent attributes, Bag of words.**

I. INTRODUCTION

The success of data mining and information retrieval techniques in structured data and semi-structured data has recently emerged in computer vision tasks including object retrieval, discovery, categorization and recognition. Graphics recognition rely on two basic steps namely the extraction and description of primitives and the graphics recognition. In order to tackle the problem of graphic symbols features description, a wide variety of descriptors have been proposed. Supervised classification is a task of mining data that consists on building a classifier from samples which are labeled by their class (learning phase), and then predict the class of new examples with the classifier (classification phase). Classical approaches for image recognition use classical classifiers such as Knn, decision trees or Bayesian networks that have already been successfully applied to many learning and pattern recognition problems. On the other hand, the growing interest in Formal Concepts Analysis (FCA) since 2000, either in the field of data mining or in knowledge representation has risen the use of Galois lattice structure. The present work is part of an ongoing effort [1] to improve the performance of symbol recognition system based on the Galois lattice classifier by introducing a novel concept that we called the Frequent Galois lattice. In this paper [1], we propose a new method of symbol description, where each symbol is described using a feature vector computed on the stable neighborhood of a set of points chosen randomly from the symbol. Secondly, we propose a new recognition approach based on a frequent Galois lattice. The originality of our approach is to recognize graphics by using a concept lattice based on frequent patterns which describe graphical symbols. Instead of using a numerical value resulting from the segmentation phase, we propose to build the classifier in terms of frequent symbolic primitives. Primitives pruning step is required in order to filter the visual dictionary and only extract the frequent patterns which appear most often in the symbols database. A Galois lattice is then constructed based not on the binary relation between {objects*attributes}, but based on the relation between {objects*frequent attributes}.

II. PROPOSED APPROACH

The originality of our approach (see Fig. 1) is that instead of using a classical Galois lattice to recognize symbols, we propose to build the Galois lattice in terms of frequent graphical patterns describing symbols. Feature selection and description is the preprocessing step of a graphics recognition system. Obviously this is a critical step in the entire scenario of a such system. Our method deals mainly with simplifying the bag of features by eliminating the least informative features and keep only those which bring information about symbols in order to build a frequent Galois lattice used as a classifier. The existing literature on primitive indexing methods are based on classical interest points detectors where a local descriptor is computed at the neighborhood of these points. Recent studies show the robustness of these methods in image processing systems. In our work we will present a suitable symbol representation as a set of interest regions computed at the neighborhood of a set of points chosen randomly from a graphic symbol. A shape descriptor is then applied for each primitive. A quantification step based on the k-means algorithm is required to build the bag of words. The obtained visual words are grouped into two sets: a set of frequent graphical patterns and a set of

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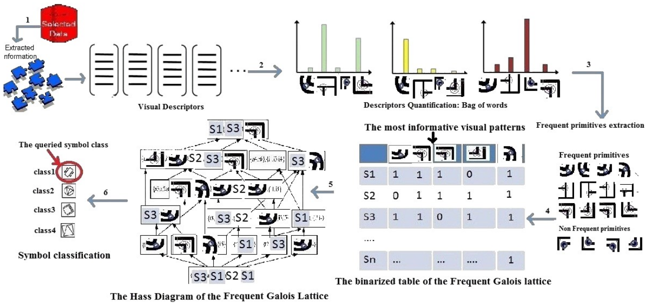

Figure 1: The proposed Graphics recognition approach using the Frequent Galois Lattice.

non frequent patterns using the frequency of appearance of each word in the whole database. The frequent item sets are used to build the concept lattice which is used to recognize symbols. Given a query symbol S_i and its corresponding frequent visual words V_i describing each primitive p_i, the Hass diagram is traversed in order to recognize the query symbol. More precisely, all the frequent concepts are visited in order to compare the attributes contained in each concept to those describing the query symbol. The concept where the query symbol belongs to, is returned as the result of the recognition process.

A. *Features extraction and description*

1) Features extraction: As noted, the first step is the feature point detection. Recently, there is a trend of using key points or local interest points for image retrieval and classification. Key points are salient primitives that contain rich local information of an image, and they can be automatically detected using various detectors and represented by many descriptors. A point of interest is defined as a point with a well-defined position and which can be robustly detected. This means that a point of interest can be a corner, but it can also be, for example, an isolated point of a maximum or a local minimum of the intensity, or a point on a curve where the curvature is locally maximal. It can also be defined as a point chosen randomly from a given graphic symbol. The quality of a point detector is often judged on its ability to detect same area in different images. In our work, we use a new algorithm to extract points from a given graphical symbol where a set of points are chosen randomly. Our algorithm finds regions in the neighborhood of a point chosen randomly, which are maximally stable [3], meaning that they have a lower variation than surrounding regions (see Fig. 2 (a)).

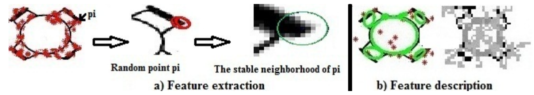

Figure 2: (a) Features extraction, (b) Features description.

2) Feature description at symbol level: In the second step, a feature vector for each point is computed. Formally speaking, given a symbol S=$\{p_1....p_n\}$ and a local descriptor f defined over the space of primitives, after applying f to each primitive we will have in return a set of features vectors f(p_i) for all i $\in$ [1, n]. A symbol is then described by a set of feature vectors describing its conforming primitives. In fact, in our approach, a symbol S is represented by a set of descriptors calculated from the neighborhood (stable regions around the point), see Fig. 2. b) of a set of points chosen randomly. A symbol S is described as follows: S $\equiv$ $\{X_i \mid Rp_i \in \Re\}$ where $\Re$= $\{ p_1, p_2, ..., p_M \}$ is the set of interest points chosen randomly, and X_i is the SIFT descriptor computed at the stable ellipse bounding p_i. The SIFT descriptor computes the gradient vector for each pixel in the feature point's neighborhood and builds a normalized histogram of gradient directions. The SIFT descriptor creates a 16*16 neighborhood that is partitioned into 16 subregions of 4*4 pixels each. A symbol is now described by a set of SIFT descriptors computed on these interest regions defined by bounding ellipses.

3) Visual vocabulary building: Symbols are composed of several primitives, indexing a symbol consists in separately and indexing each of its primitives. Primitives descriptors are then grouped into a large number of clusters so that those with similar descriptors are assigned into the same cluster. By treating each cluster as a visual word that represents the specific local pattern shared by key points in that cluster, we have a visual-word vocabulary describing all kinds of local image patterns. As shown in Fig. 3, the distribution of visual words is not uniform, that's means there is a larger percentage of uninformative visual patterns that are not frequent and may bring large uncertainties and ambiguities in the representation which should be eliminated from the visual vocabulary. One possible solution to resolve the ambiguity of visual patterns is to extract only the frequent visual words having an appearance frequency parameter in the database greater than a given threshold. In other words, the visual dictionary is likely to be much less ambiguous but much discriminative. Therefore, it is of great interest to automatically discover these frequent visual patterns in order to build a frequent Galois lattice with a reasonable size and a good recognition rate. In our work, we study this issue by simply finding frequent visual words. Although this is a good starting point of image data mining, there are many challenges that need to be overcome. By discovering the visual dictionary Ω ($\Omega_{Freq} \cup \overline{\Omega}_{Freq}$) (see Fig. 3) and summarizing it, we obtain a small set of meaningful visual patterns Ω_{Freq}, its probability of appearance in the database is greater than a given threshold. Compared with visual words in the set $\overline{\Omega}_{Freq}$, these visual words patterns have much less ambiguities because they are the most discriminative primitives. Based on Ω, we can divide Ω into two disjoint subsets, $\Omega = \Omega_{Freq} \cup \Omega_{NonFreq}$, where for any visual pattern $P_i \in\Omega$, we have $P_i \subseteq \Omega_{Freq}$ if Pr[P_i] $\geq$ *minsupp* (where *minsupp* is a given threshold and Pr[P_i]

is the probability of appearance of the visual word P_i in the database. Ω_{Freq} is the input of our Galois lattice classifier based on the binary relation {Symbols*Ω_{Freq}}.

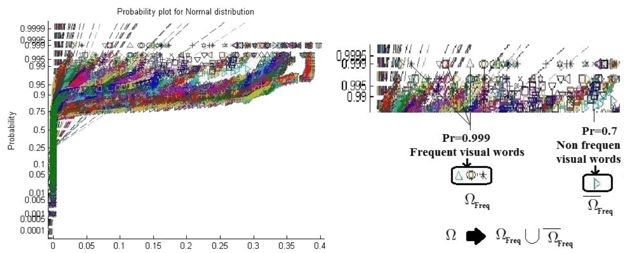

Figure 3: The filtering process of the vocabulary Ω.

B. Symbol recognition using a Frequent Galois lattice

In the field of graphics recognition, the performance of systems not only depends on the description technique but also on which kind of data structure is used to provide efficient access and organize the feature description. In our approach, we use the Galois lattice structure.

1) Mathematical foundations of the Galois Lattice: The Galois lattice is the foundation of a set of conceptual classification methods. Each concept of the lattice L, derived from the context *K*=(O,A,I), is a couple (X,Y) composed of an object X $\in$ *O* and an attribute Y $\in$ *A*. Concepts are complete couples verifying I, which means that the following two conditions are satisfied: a) Y= *f*(X) ={a $\in$ A$\|\forall$ o $\in$ X, oIa}; b) X= *g*(Y) ={o $\in$ O$\|\forall$ a $\in$ Y, oIa}. The functions *f* and *g* constitute a Galois connection between *O* and *A*. The concept lattice L on *K*= (O,A,I) is made up of all complete couples with the partial order $\leq$, where: (X1,Y1) $\leq$ (X2,Y2) $\Leftrightarrow$ X1 $\subseteq$ X2.

2) The new Frequent Galois Lattice: Our approach is to eliminate the step of discretization attributes by using the symbolic representation of objects and the originality is to extract attributes the most frequent and the most informative from the visual dictionary in order to eliminate the least discriminative patterns. The new Galois lattice is called a frequent Galois lattice and built not in terms of all graphical patterns describing the symbol but in terms of frequent graphical patterns. Our approach is defined as follows: a given symbol will be represented by a vector of visual words. An extraction step of frequent attributes is required before the phase of construction of the concept lattice which is obtained from the binary relation between the frequent visual dictionary and the set of graphic symbols. The probability of appearance of each visual word is used in order to prune the non frequent patterns. The proposed method uses a three step mechanism: a) the first step consists on finding graphical patterns frequent in the set of descriptions of the symbols (frequent visual words); b) the second step uses the frequent primitives to build the binarized table of the frequent Galois lattice (see Fig. 1); c) finally, empty and redundant concepts are pruned during the step of constructing the Galois lattice.

Algorithm 1 The extraction of frequent itemsets

Input Ω, $\Pr_{i,j}$[Att_i, S_j], where ($Att_i \in \Omega$), *minsup*
Initialize the set of concepts having the size=1
While the set of concepts not empty **do**
Pruning step
a) Calculate the support of candidates
b) Prune the set of concepts whose frequency of appearance *freq* $\leq$ *minsup*
c) Calculate the closing of the retained candidates
d) The Hass diagram construction step
End While
Output Ω_{Freq}: The set of frequent attributes

3) The traversal of the Hass diagram of the Galois lattice for the classification phase: Usually there are no criteria or parameters to be considered for the construction of lattice concepts, since it represents all the possible combinations between objects and attributes, however in our approach the concept lattice is built using the binary relation R between objects and frequent visual words. Given a query symbol, and its visual words, the Hass diagram is traversed in order to recognize the query symbol. A traversal of the Hass diagram often leads to visit all the concepts containing a set of attributes (primitives) describing the query symbol. The node containing the primitives of the query is returned as the result of the recognition process.

III. Experimental Results

We study the performance of a graphics recognition system based on the approach described in section 2. The GREC2003 database is partitioned into a training set of 1000 symbols and a test set of 500 query symbols. For the step of extracting frequent patterns from the visual dictionary, the chosen threshold *minsupp* is set to θ = 2/3*$\|\Omega\|$, where $\|\Omega\|$ corresponds to the size of the visual vocabulary described in section A (Figure 3). A visual word w_i is considered as a frequent pattern if it appears in a set of symbols S_j with a probability $\Pr_{i,j}(w_i, S_j) \geq \theta$. The set of the frequent graphical patterns is Ω_{Freq}. We set the vocabulary size $\|\Omega\|$=500. The experiment presented in Fig. 4, aims to evaluate the performance of our recognition system achieved using the Galois lattice classifier combined first, with the entire visual dictionary Ω, and secondly with the filtered visual dictionary Ω_{Freq} representing only the frequent visual words. We present the obtained recognition results for the whole recognition experiment using the whole dictionary Ω describing symbols (red bins). The obtained recognition rates when considering just Ω_{Freq} which correspond to the set of frequent visual words used to build the frequent Galois lattice classifier (FGL) is shown by blue bins. As we can appreciate, the frequent classifier based on $\|\Omega_{Freq}\|$ (FGL:{Symbols, Ω_{Freq}}) provides the best recognition rate in comparison with the one built using the whole set of attributes $\|\Omega\|$ (GL:{Symbols, Ω})[1]. This experiment allows to evaluate: a) The recognition rate

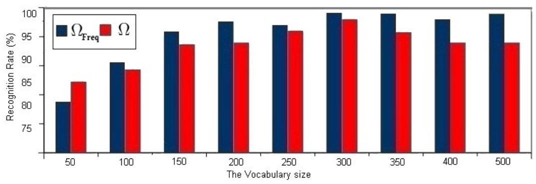

Figure 4: Evolution of the recognition rate using the Galois lattice combined respectively with Ω and Ω_{Freq} as a function of the vocabulary size.

obtained by the Frequent Galois Lattice $\text{FGL}_{\Omega_{Freq}}$ when we take into account only the filtered dictionary in terms of frequent visual words. We remark that the results provided by combining the Galois lattice with the filtered dictionary Ω_{Freq} are significantly higher than the results provided by the whole dictionary Ω. This can be explained by the adequacy and the sufficiency of the information provided by the frequent patterns independently from the rare patterns of the dictionary whose probability of appearance in the symbol database do not exceed the given threshold *minsupp*. The recognition rate obtained by the GL_{Ω} [1] using the whole dictionary. The recognition rate of the Galois lattice based on the totality of the visual vocabulary ($\Omega_{Freq} \cup \Omega_{NonFreq}$) is lower than the recognition rate provided by the FGL based only on Ω_{Freq}. This result proves the impact of the frequent patterns on the performance of the classifier. b) The evolution of the recognition rate related to the size variation of the visual dictionary (see x axis). Filtering the vocabulary in terms of frequent visual words can lead to reduce the size of the vocabulary of several percentages of its original size between 10% to 90% by increasing θ (since θ depends on the size of the vocabulary Ω) and pruning the words which are less informative in terms of discrimination capability and assess the classification performance of each experiment. The x axis shows the size of the dictionary obtained following several filters: 10% for 50 visual words, 20% for 100 visual words, ... and 90% for 500 visual words. The recognition rate improves with increasing the number

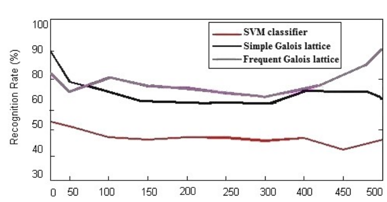

Figure 5: Evaluation of the recognition rate as a function of the number of attributes using the GL_{Ω}[1], $\text{FGL}_{\Omega_{Freq}}$ and the SVM classifier (in this experiment, θ=2/3, $\|\text{NbSymb}\|$=1500, Ω varying from 50 to 500 visual words and Ω_{Freq} is the set of frequent visual words having a probability of appearance in the symbols database greater than $\theta * \|\Omega\|$).

of visual patterns. When the vocabulary size is set to 50 visual words (it corresponds to 10% of the initial size of the dictionary), the recognition rate is 81% using our approach $\text{FGL}_{(Symbols,\Omega_{Freq})}$ instead of 84% for the $\text{GL}_{(Symbols,\Omega)}$. This can be explained by the fact that there is not a sufficient number of characteristics that can be extracted from the visual dictionary Ω, whereas during the remainder of the experiment, the recognition rate increases much faster when the number of frequent features is increasing and reaches 98.04% for the FGL compared with 94.6% for the GL_{Ω} [1]. The $\text{FGL}_{\Omega_{Freq}}$ provides the best recognition rates compared with the classifier GL_{Ω} obtained using the set of attributes Ω. We conclude that a vocabulary can be decreased until a certain threshold without loss of classification accuracy, which implies that the percentage of informative patterns in the bag of words is much larger than the uninformative patterns (see Fig. 5). At the beginning of the experiments, we remark that the simple Galois lattice GL_{Ω} [1] is more performer than $\text{FGL}_{\Omega_{Freq}}$ and this is due to the lack of frequent patterns but when the size of the dictionary is increasing, the performance of $\text{FGL}_{\Omega_{Freq}}$ is remarkable in comparison with GL_{Ω}. The fact that $\text{FGL}_{\Omega_{Freq}}$ is significantly better than GL_{Ω} implies that frequent visual words widely spread among symbols are more informative than rare visual words in terms of discriminative power. It is also partially explained why the robustness of the feature extraction method. In our experiments, we extract randomly 300 points from a graphical symbol and after the filtering step we keep only an average of 45 key points. Figure

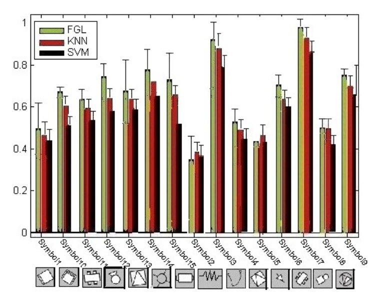

Figure 6: Evaluation of the recognition rate (%) of different classifiers.

6 shows an evaluation of the frequent Galois lattice in comparison with classifiers usually used in the literature in terms of recognition rate. Each classifier is trained in order to determine the presence of a specific concept or object. The performance of $\text{FGL}_{(Symbols,\Omega_{Freq})}$ is also higher (98.4%) in comparison with others classifiers such us the Support Vector Machines (SVM) (its highest recognition rate is 82.5%) and the knn classifier (reaches 95% in terms of recognition rate).

IV. Evaluation of the approach

As mentioned previously, in [2] the Galois lattice is generally based on a phase of attributes discretization, this step is important if we use the numerical signature, but it is eliminated when we work with the visual dictionary. We compared our approach to [2] in order to evaluate its performance (see Table 1). As we can see in Table 1, the performance of the frequent concept lattice classifier $\mathrm{FGL}_{(Symbols,\Omega_{Freq})}$ resulting from our approach is higher (98.4%) than the classical concept lattice $\mathrm{GL}_{(Symbols,\Omega)}$ (96.08%) [1] and higher than the approach [2] based on numerical signatures as a representation method (94.62%). This is due to the criteria of frequency of a primitive used in order to eliminate the least informative primitives which allows to group symbols sharing the same frequent primitives into the same class. This approach guarantee a good rate of classification and a reduced processing time during the traversal of the Hass diagram (109.7s for our approach instead of 231.74s for [2] and 153.85s for the Galois lattice based on the whole set of attributes). Moreover, the number of concept is reduced when using our approach (2100 nodes) instead of 3170 nodes for the GL and 4230 nodes for [2]. This is due to the step of empty and non frequent concepts pruning. The evaluation of the complexity of such a classifier in terms of number of nodes is shown in Fig. 7 also. As we can see, the main disadvantage of a Galois lattice is its size which can be very large in real applications. In our approach, we propose to reduce the size of the lattice by simplifying the features describing objects, but we try to maintain its structure and sufficiency. The FGL is better than the GL in terms of size and complexity. Our results are better because an elimination of the least informative patterns from the visual dictionary offers a reasonable size (see the number of concepts in Table 1 (row 1) and see Fig. 7). Since symbols of the same class are grouped in the same concepts. It can be seen in Table 2 that the method used to represent visual patterns of a graphical symbol shows good results in terms of precision. This shows that features extraction and description method are effective techniques in symbols classification. Among different features description methods in terms of recognition rate, our method based on SIFT descriptor applied at points chosen randomly (98.4%) is top performer and provides the best results. In our approach, the chosen local descriptor is calculated from a stable neighborhood of a sample point shows good results. In Table 1: (row3, column2) and (row3, column3), we can appreciate that the recognition rate obtained using the FGL combined with our method of features extraction and description (based on randomly chosen points) is greater than the recognition rate of [2] which used the classical interest points detectors.

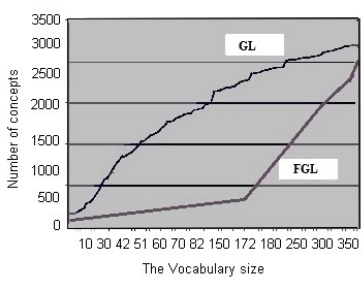

Figure 7: Comparison between the size of the two classifiers: $\mathrm{FGL}_{\Omega_{Freq}}$, GL_{Ω} as a function of the size of the dictionary.

Table I: Performance evaluation of GL[1], GL[2] and FGL.

Criteria/ Used Approach	GL[1]	FGL	Approach in [2]
Number of concepts	3170	2100	4230
Processing Time (s)	153.85	109.7	231.74
Recognition rate(%)	96.08	98.4	94.62

Table II: Comparison between different methods for primitives description.

Descriptor/Criteria	Recognition rate (%)	Precision	Recall
Our approach	**98.4**	0.97	0.52
SIFT	94.4	0.856	0.41
Shape Context	95.6	0.9	0.27
Fourier Descriptor	89.3	0.75	0.32

V. CONCLUSION AND FUTURE WORK

In this paper, we have proposed an original approach for graphics recognition based on the frequent Galois lattice built using the frequent visual words that bring large information about a given graphics. Graphical patterns which appear frequently in the graphics database guarantee a satisfiable discrimination criteria for the frequent concept lattice classifier. A combination between the filtered visual dictionary Ω_{Freq} instead of the whole dictionary Ω with of the new proposed prototype which is the Frequent Galois lattice has been proposed. The experimental results show the relevance and robustness of our approach. In addition, the proposed method for primitive description showed good results. The main novelty of the paper is the use of frequent graphical patterns to build our classifier which guarantee a high recognition rate and a reduced size and reasonable processing time during the recognition process. Our work enlarges and expands the domain of formal concept analysis by demonstrating that the Galois lattice can be used for symbol recognition.

REFERENCES

[1] Amani Boumaiza and Salvatore Tabbone. A novel approach for graphics recognition based on galois lattice and bag of words representation. In *ICDAR*, pages 829–833, 2011.

[2] Mickaël Coustaty, Stéphanie Guillas, Muriel Visani, Karell Bertet, and Jean-Marc Ogier. On the joint use of a structural signature and a galois lattice classifier for symbol recognition. In *GREC*, pages 61–70, 2007.

[3] Per-Erik Forssén and David G. Lowe. Shape descriptors for maximally stable extremal regions. In *ICCV*, pages 1–8, 2007.