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Walsh, Texture and GIST Descriptors with Bayesian Networks for Recognition of Tifinagh Characters

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ABSTRACT
This paper provides an approach to automatically recognize the Tifinagh characters. The proposed recognition system is based on Texture, Walsh transformation and GIST descriptors as feature extraction methods while the Bayesian Networks are used as a classifier. A comparative study between the Texture descriptor, Walsh transformation and GIST descriptor is given. The experimental results are obtained using a character database of isolated Amazigh characters. A recognition rate of 98.18% is achieved using GIST descriptors.

General Terms
Pattern Recognition, Machine learning.

Keywords
Character recognition; texture; GIST; Walsh transformation; Bayesian networks; Tifinagh database.

1. INTRODUCTION
The Optical Character Recognition (OCR) is a rapidly expanding field in several areas where the text is the working basis. In general, a character recognition system consists of several phases as stated in many recent works [1, 2, 3, 4, 5, 6, 7, 8, 9]. The extraction phase focuses on the release of attributes from an image. The effectiveness of the system is based on the results given by the classification phase. The objective of this paper is to produce this automated characters recognition system. The tifinagh characters recognition system based on the texture, Walsh transformation and GIST descriptors is introduced. The Bayesian network is used as a classifier.

The rest of the paper is organized as follows. The Section 2 presents the texture, Walsh and GIST features extraction method. The Section 3 is reserved for the recognition of tifinagh characters by using a Bayesian network classifier while the Section 4 is reserved to present and discuss the experimental results of the tifinagh characters recognition system. Finally, in the last section, the principal conclusion concerning the proposed approach is given in addition to the possible future works.

2. TEXTURE, WALSH AND GIST DESCRIPTORS
The feature vector must be extracted carefully from an input image character in order to reduce the rich content and large data of character images while maintaining and preserving the content representation of the entire character image. Therefore, the feature extraction task can decrease the processing time.

Tifinagh characters are the set of alphabets used by the Amazigh population in morocco and Algeria. The Moroccan Royal Institute of Amazigh Culture (IRCAM) has normalized the Tifinagh alphabet of thirty-three characters as shown in Figure 1.

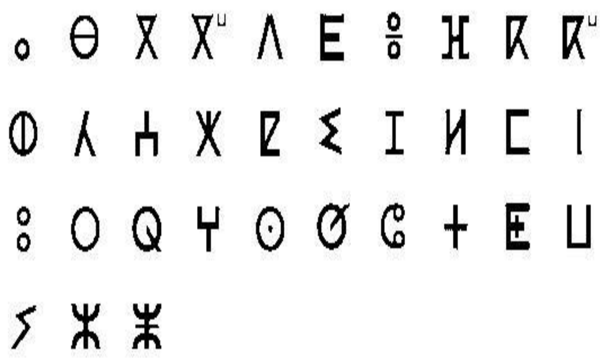

Fig.1: Thirty-three Tifinagh characters adopted by the Moroccan Royal Institute of Amazigh Culture (IRCAM).

The Tifinagh alphabet has several characters that can be obtained from others by a simple rotation, which makes invariant descriptors commonly used less effective. For this reason, we used a texture descriptors and GIST descriptors.

All the features descriptors are extracted for all the tifinagh characters in a reference database.

2.1 Texture Descriptors
The texture descriptor is extracted using the co-occurrence matrix introduced by Haralick in 1973 [10]. So for a grayscale image I of size $N \times N$, for $(k, l) \in [1, \cdots, N]^2$ and

$(a\,,b)\in[1,\cdots,G]^2$, the co-occurrence matrix $M_{k\,,l}[I]$ of the character image I is defined by:

$$M_{k,l}(a,b)=\beta\sum_{i=1}^{N-k}\sum_{j=1}^{N-l}\delta\left(I(i,\,j)-a\;,\,I(i+k,\,j+l)-b\right)$$

Where δ is the unit pulse defined by:

$$\delta(x\;,\,y)=\begin{cases}1 & if \quad x=y=0\\ 0 & else\end{cases}$$

And

$$\beta=\frac{1}{(N-k)(N-l)}$$

As they measure local interactions between pixels, they are sensitive to significant differences in spatial resolution between the images. To reduce this sensitivity, it is necessary to normalize these matrices by the total number of the considered co-occurrences matrix:

$$M_{k\,,l}([I],\,a\,,b)=\frac{M_{k\,,l}([I],\,a\,,b)}{\sum_{i=0}^{T-1}\sum_{j=0}^{T-1}M_{k\,,l}([I],\,i\,,\,j)}$$

Where T is the number of quantization.

To reduce the large amount of information of these matrices, the 14 Haralick indices [10] of these matrices are used.

2.2 GIST descriptors

In computer vision, GIST descriptors are a representation of a low-dimensional image that contains enough information to identify the scene in an image. The GIST descriptors allow a very small size representation of an image. These descriptors were introduced by Oliva and Torralba in 2001 [11, 12]. They can represent the dominant spatial structure of the scene from a set of perceptual dimensions. The authors have tried to capture the gist descriptor of the image by analyzing the spatial frequency and orientation. The global descriptor is constructed by combining the amplitudes obtained at the output of the K Gabor filters [13] at different scales E and orientations O. To reduce the feature vector size, each filtered output image is scaled and divided into N * N blocks (N between 2 and 16), which gives a vector of dimension N * N * K * E * O. This dimension can be further reduced by a principal component analysis (PCA), which also gives the weights applied to different filters [14].

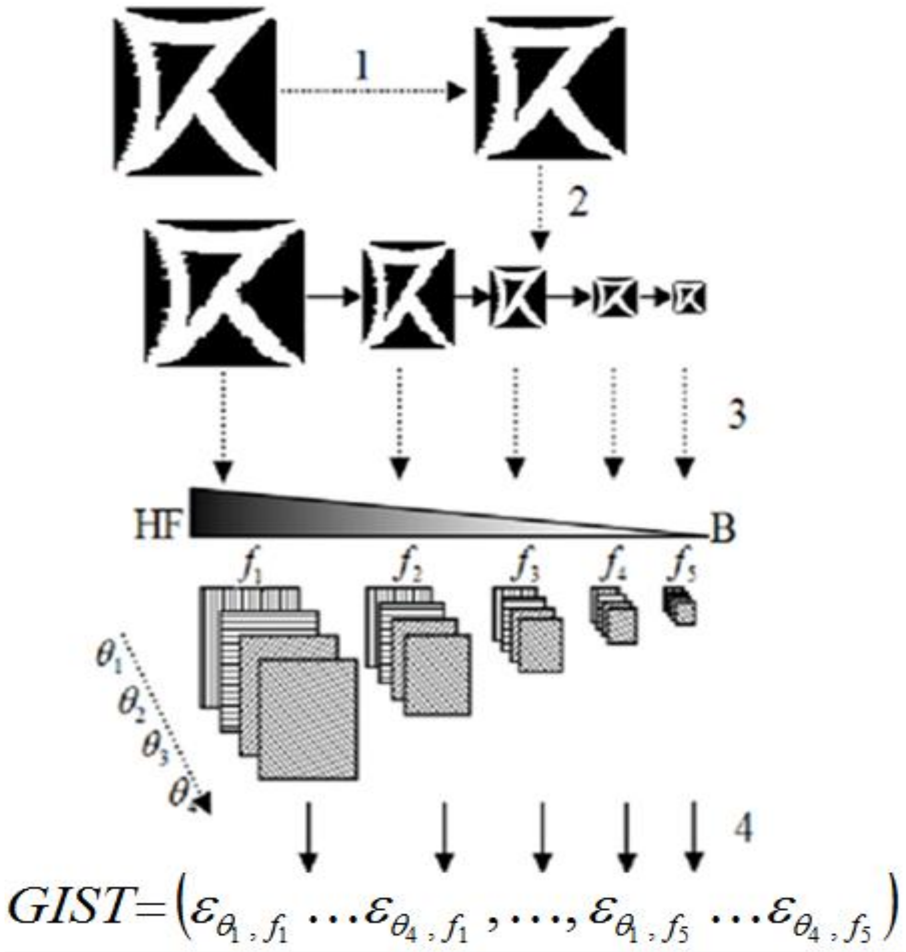

Fig.2: Block diagram for computation and extraction of GIST Descriptor.

As specified above, the Figure 2 presents a block diagram summarizing the different steps for the computation and extraction of GIST descriptors. After the pre-processing step of the input character image, the next step consists on changing the character image into different scales and orientations. Finally, the features vectors are calculated for each scale, orientation and frequency. Those features vectors are combined to form a global feature descriptor which is reduced by a principal component analysis (PCA).

2.3 Walsh Transformation

The Walsh transformation W (u, v) can be calculated using the following formula:

$$W(u,v) = \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y) g(x,y,u,v)$$

Where f(x, y) is intensity of the pixel with the coordinates (x, y) in the original binary image, u, v = 0, 1… N-1. The size of the image f is N x N, and function g is the kernel function of the transformation and has the following form:

$$g(x,y,u,v) = \frac{1}{N}\prod_{i=0}^{n-1}(-1)^{b_i(x)b_{n-i-1}(u)+b_i(y)b_{n-i-1}(v)}$$

Where $b_i(x)$ is the i^{th} bit in the binary expansion of x, so it is equal either 0 or 1, and $N=2^n$.

The Walsh transform is unique in the sense that if two considered binary images are different, the corresponding feature vectors are also different. Since the Walsh transformation is invariant under size changes, to perform and calculate the Walsh transformation, the original image is firstly changed and resized to the size of 2^n x 2^n for n=8.

3. BAYESIAN NETWORK CLASSIFIER

Bayesian networks are based on a probabilistic approach governed by Bayes' rule. The Bayesian approach is then based on the conditional probability that estimates the probability of occurrence of an event assuming that another event is verified. A Bayesian network is a graphical probabilistic model representing the random variable as a directed acyclic graph. It is defined by [15]:

- $G=(X, E)$, Where X is the set of nodes and E is the set of edges, G is a Directed Acyclic Graph (DAG) whose vertices are associated with a set of random variables $X=\{X_1, X_2, \cdots, X_n\}$;
- $\theta=\{P(X_i \mid Pa(X_i))\}$ is a conditional probabilities of each node X_i relative to the state of his parents $Pa(X_i)$ in G.

The graphical part of the Bayesian network indicates the dependencies between variables and gives a visual representation tool of knowledge more easily understandable by users. Bayesian networks combine qualitative part that are graphs and a quantitative part representing the conditional probabilities associated with each node of the graph with respect to parents [15].

Pearl and all [16] have also shown that Bayesian networks allow to compactly representing the joint probability distribution over all the variables:

$$P(X) = P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i))$$

Where $Pa(X_i)$ is the set of parents of node X_i in the graph G of the Bayesian network.

This joint probability could be actually simplified by the Bayes rule as follows [17]:

$$\begin{aligned} P(X) &= P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P(X_i \mid Pa(X_i)) \\ &= P(X_n \mid X_{n-1}, \cdots, X_1) \times \cdots \times P(X_2 \mid X_1) \times P(X_1) \\ &= P(X_1) \times \prod_{i=2}^{n} P(X_i \mid X_{i-1}, \cdots, X_1) \end{aligned}$$

The construction of a Bayesian network consists in finding a structure or a graph and estimates its parameters by machine learning. In the case of the classification, the Bayesian network can have a class node C_i and many attribute nodes X_j. The naive Bayes classifier is used in this paper due to its robustness and simplicity. The Figure 3 illustrates its graphical structure.

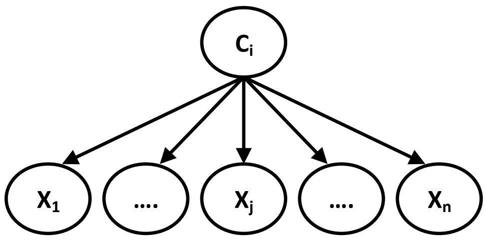

Fig.3: Naive Bayes classifier structure.

To estimate the Bayesian network parameters and probabilities, Gaussian distributions are generally used. The conditional distribution of a node relative to its parent is a Gaussian distribution whose mean is a linear combination of the parent's value and whose variance is independent of the parent's value [18]:

$$P(X_i \mid Pa(X_i)) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left\{ \frac{-1}{2\sigma_i^2}\left(x_i - \left(\mu_i + \sum_{j=1}^{n_i} \frac{\sigma_{ij}}{\sigma_j^2}(x_j - \mu_j) \right) \right)^2 \right\}$$

Where,

- $Pa(X_i)$ Are the parents of X_i;
- μ_i , μ_j , σ_i *and* σ_j are the means and variances of the attributes X_i and X_j respectively without considering their parents;
- n_i is the number of parents;
- σ_{ij} is the regression matrix of weights.

After the parameter and structure learning of a Bayesian network, The Bayesian inference is used to calculate the probability of any variable in a probabilistic model from the observation of one or more other variables. So, the chosen class C_i is the one that maximizes these probabilities [19 , 20]:

$$P(C_i|X)=\begin{cases} P(C_i)\prod_{j=1}^{n} P\left(X_j|Pa(X_j),C_i\right) & if \quad X_j \ has\ parents \\ P(C_i)\prod_{j=1}^{n} P\left(X_j|C_i\right) & else \end{cases}$$

For the naive Bayes classifier, the absence of parents and the variables independence assumption are used to write the posterior probability of each class as given in the following equation [21]:

$$P(C_i|X)=P(C_i)\prod_{j=1}^{n} P\left(X_j|C_i\right)$$

Therefore, the decision rule d of an attribute X is given by:

$$\begin{aligned} d(X) &= \arg\max_{C_i} \ P(C_i|X) \\ &= \arg\max_{C_i} \ P(X|C_i)\,P(C_i) \\ &= \arg\max_{C_i} \ P(C_i)\prod_{j=1}^{n} P\left(X_j|C_i\right) \end{aligned}$$

The class with maximum probability leads to the suitable character for the input image.

4. EXPERIMENTS AND RESULTS

4.1 Experiments

In the experiments, for each character image, the number of input features extracted using Texture extraction method is 14x4 = 56 while the number of input features extracted using GIST extraction method is 32. These inputs are presented and feed to the classifier; which is the Bayesian network in order to select the appropriate keywords from the reference database.

The accuracy of the recognition system is evaluated by the precision rate which is the number of correct results divided by the number of all returned results.

All the tests are performed using a database containing a set of 33 reference characters and 165 image characters [22]. The proposed system has been implemented and tested on a core 2 Duo personnel computer using Matlab software.

4.2 Results and Discussion

The comparison of the general recognition rates between the Texture descriptors, GIST descriptors and Walsh transformation descriptors, used as feature extraction methods, is illustrated in the Table 1. When using the Bayesian network as a classifier, the learning and total execution times are also given in order to know the fastest descriptor. The experimental results showed that the recognition rates of the Bayesian network classifier based on GIST descriptor is higher than the recognition rate based on Texture descriptors and Walsh transformation descriptors.

Table 1. Recognition and Error Rates with Learning and Execution Times of Texture, Walsh transformation and GIST Descriptors using Bayesian Network classifier.

Extraction Method	Learning Time (s)	Execution Time (s)	Recognition Rate (%)	Error Rate (%)
Texture	12.02	528.65	86.06	13.94
GIST	7.12	298.62	98.18	01.82
Walsh	11.10	476.88	69.09	30.91

The following figures give the confusion matrix of each descriptor.

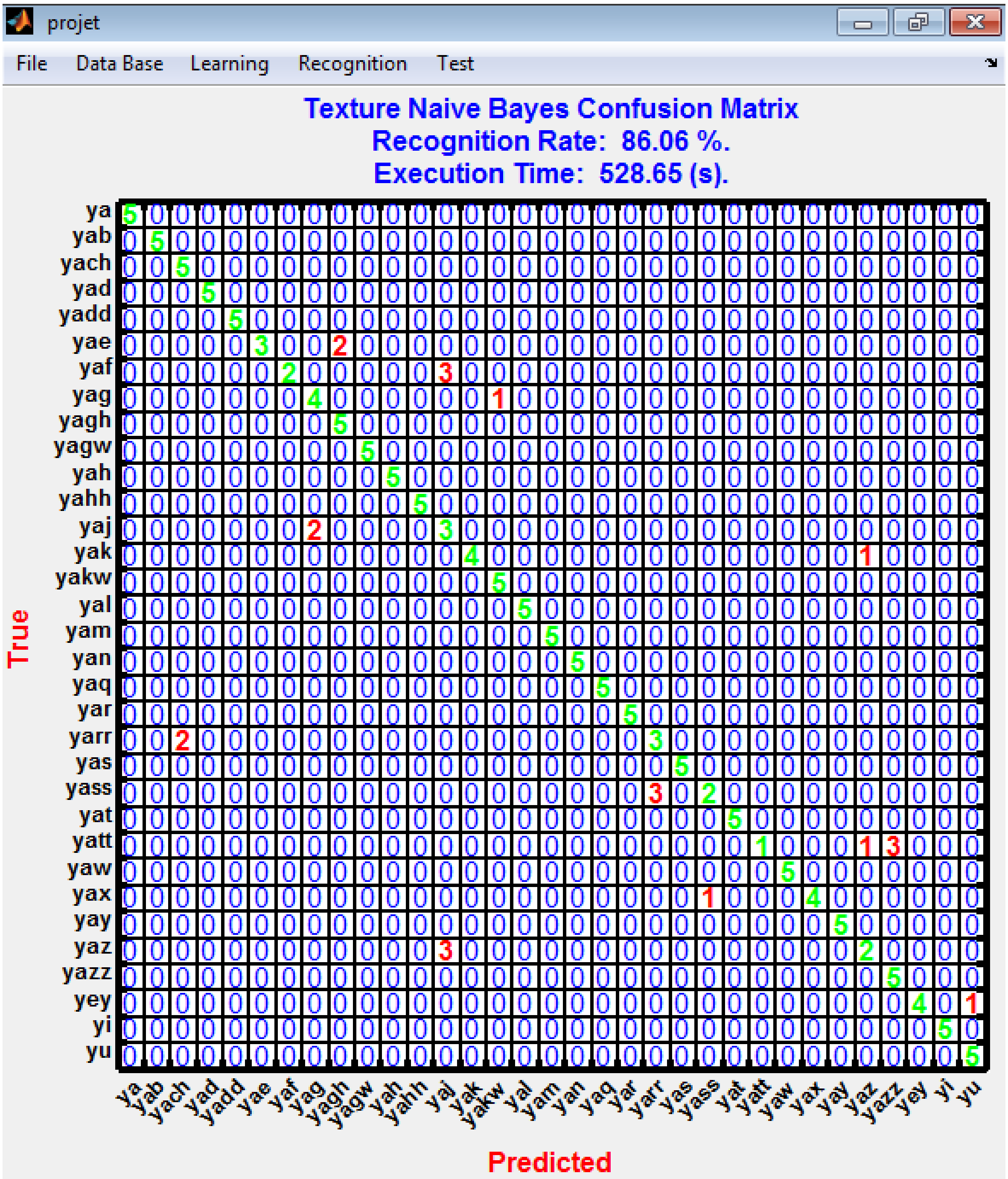

Fig 4: Confusion matrix of the recognition system based on the Texture descriptor and Bayesian network classifier.

The Figure 4 gives the confusion matrix of the recognition system based on the Texture descriptor and the Bayesian network classifier while the Figure 5 gives the confusion matrix of the recognition system based on the GIST descriptor and the Bayesian network classifier in the case of using k-means segmentation directly and the case of regrouping region.

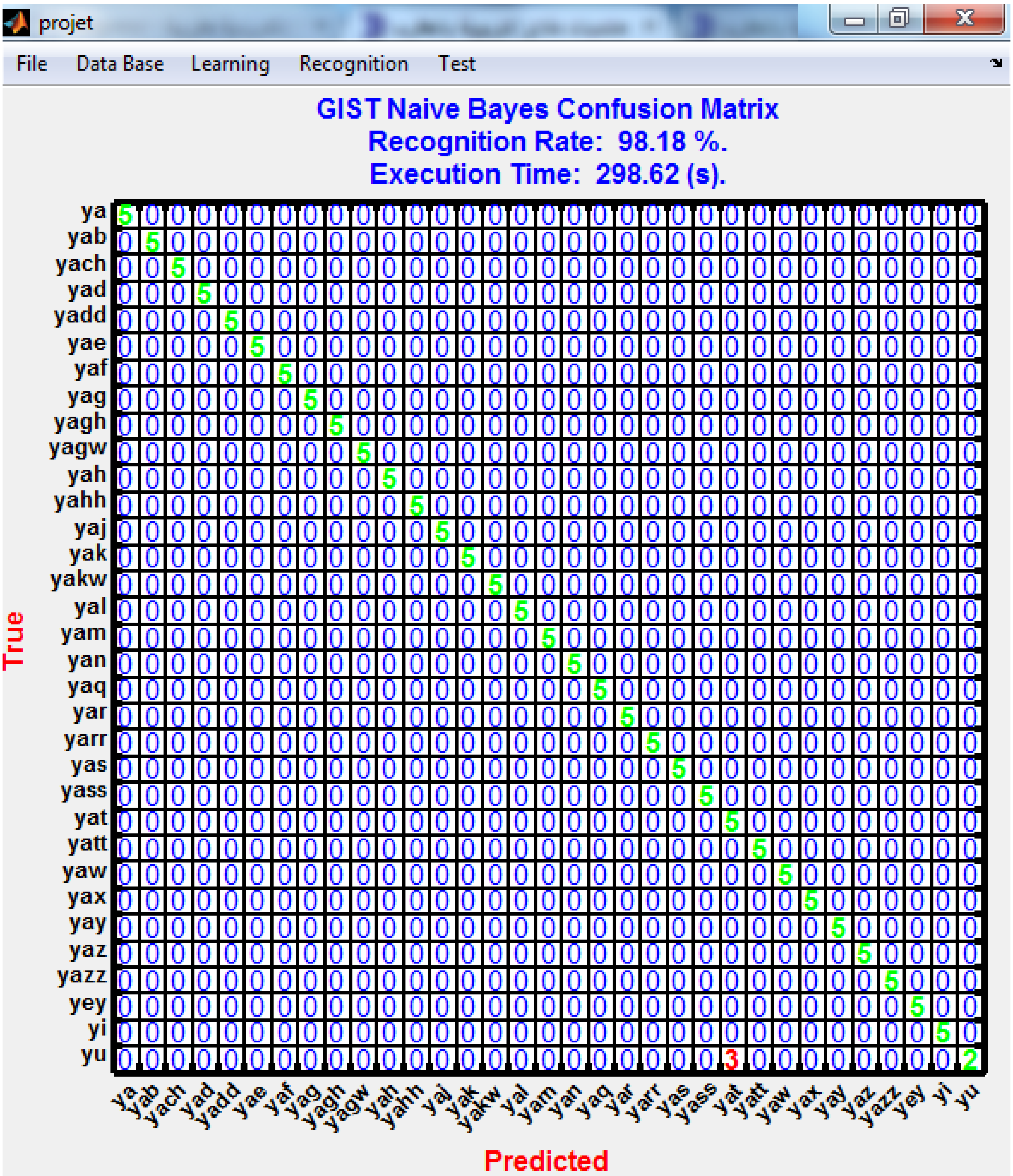

Fig 5: Confusion matrix of the recognition system based on the GIST descriptor and Bayesian network classifier.

The Figure 6 illustrates the confusion matrix of the recognition system based on the Walsh transform and a Bayesian network classifier.

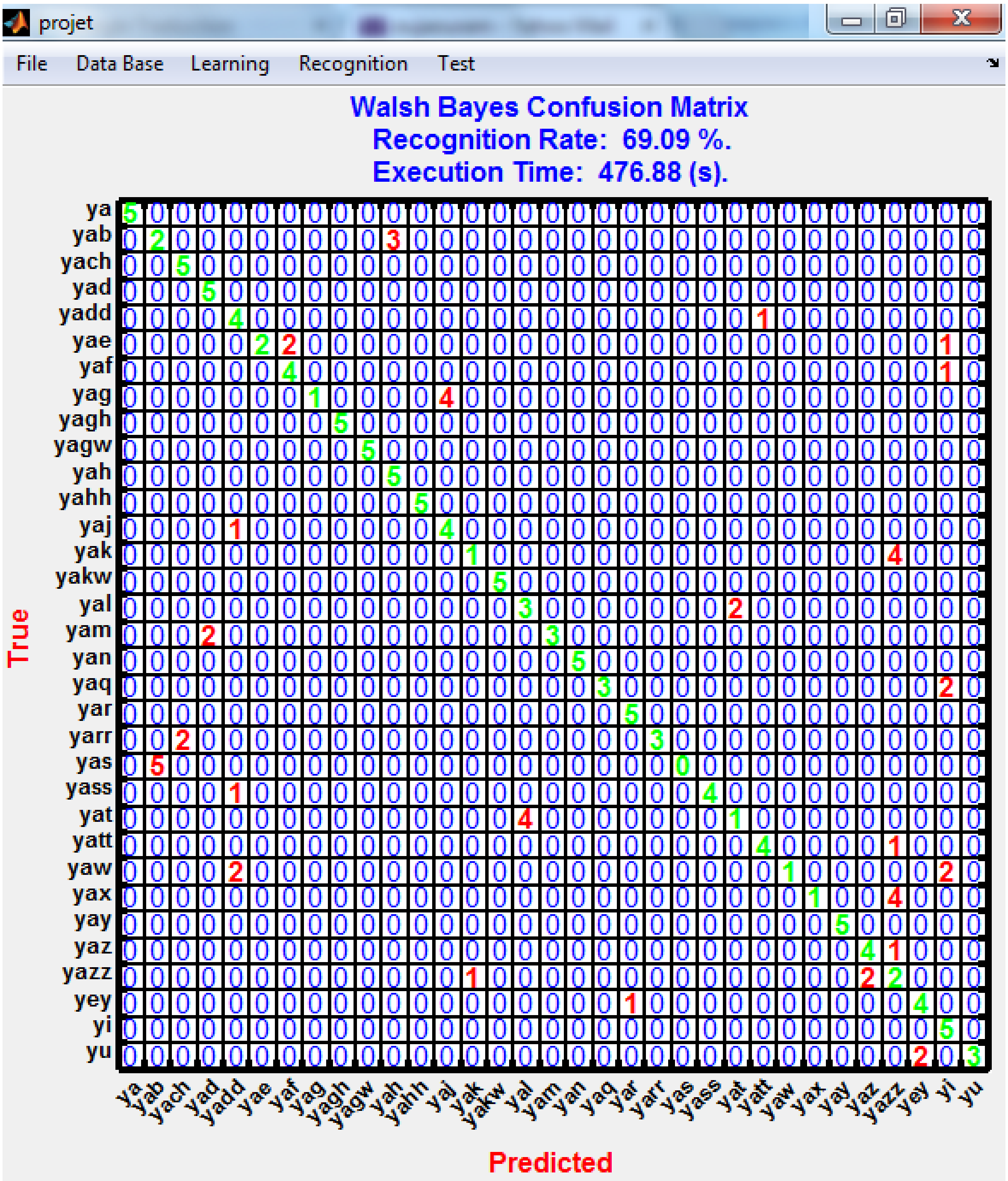

Fig 6: Confusion matrix of the recognition system based on the Walsh transformation descriptor and Bayesian network classifier.

In addition to their good recognition rates, the processing time (execution and learning times) of the GIST descriptors is considerably less than the processing time (execution and learning time) of the Texture and Walsh transformation descriptors. This is what makes GIST descriptor an effective means of description and recognition compared with the other descriptors.

5. CONCLUSION

In this paper, the Tifinagh character recognition system based on the texture, Walsh transform and the GIST descriptors as extraction algorithms and a Bayesian networks as a classifier is presented. For this recognition system, the effect of using different extraction algorithm is discussed. The performance of the proposed system has been experimentally analyzed. The successful experimental results proved that the proposed recognition system gives good results for the GIST descriptors. However, some character remains a challenge that stills need more attention in order to increase precision and accuracy of the Tifinagh character recognition system. Also, the tifinagh character segmentation must be considered in the future work for more accuracy of the possible online recognition system.

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