A Fuzzy ARTMAP Module for Graphics Symbols Recognition

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Abstract

This paper presents a method for recognizing graphics symbols of electronic components in a database of circuit layouts. The method is based on the One-Class Problem approach on our ability to recognize a 2D-objects without making an explicit decomposition. To satisfy these requirements, a Fuzzy ARTMAP recognition module was developed with the objective of recognizing the graphics symbols of 19 electronic components. Each Fuzzy ARTMAP was trained with 2D images of graphic symbols of one component only (positive patterns only). The recognition module was then used to search for a specific component in a database of 30 images of circuit layouts. The training and test sets contained, respectively, 380 images (20 images/component), and 2051 images (an average 0f 108 images/component). Experimental results show an average percentage error of 3.49%.

1. Introduction

The growing use of Electronic Document Management Systems (EDMS), in offices and industry, to store and manage a huge database of document images, has stimulated the interests of many researchers and developers to come up with computational tools to search for specific pictorial information in image databases.

At the Laboratory of Document Image Analysis and Neural Networks (LADIANN) of the Pontificia Universidade Católica do Paraná (PUC-PR), research has been conducted to develop a page-reading system for interpreting and reconstructing technical drawings from scanned images. The system must be autonomous, capable of learning from positive examples only, adaptive to changes in its environment, and able to operate on-line. Initially, we are concerned with electronic circuit layouts similar to those shown in figure 1. Those types of circuits have pre-defined structures, i.e., the size and shape of each component is almost constant in all layouts. The structure of the complete system (currently under-development) is composed of several modules, each of which is developed separately. In this work we are concerned with the recognition module, whose objective is to recognize the 2-D shapes (Graphics Symbols) of electronic components in circuit layouts. At this stage of our work we are concerned with 19 components only, namely: resistors, capacitors, inductors, opamps (Operational Amplifiers), transistors, diodes, and logic gates (NOT, AND, NAND, OR, NOR and XOR). The graphics symbols of most of these components are shown in figure 2.

1.1. The Method

As mentioned above, we are interested in recognizing graphics symbols that are scale-invariant, exist in a pre-defined orientation and composed of simple constituents as shown in figure 2. When recognizing such patterns, the question becomes that of deciding what is the appropriate strategy to solve the problem in hand: Classical or Computational Neural Networks approach.

In graphics application, one could group the classical approaches of recognizing the graphic symbols under three categories: syntactical pattern recognition [1][2], graph rewriting technique [3][4], and knowledge-directed [5][6]. Those approaches, explicitly, decompose the graphics symbol into its constituents (lines, curves, circles, etc.) and then recognize each constituent individually. The final decision is reached using some sort of grammars, graph representation or *a priori* rules. These approaches require a lot of pre-processing operations

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and, hence, may be computationally expensive, especially when dealing with simple shapes. However, they are efficient when dealing with complex engineering drawings or when recognizing graphics symbol given its definition. . For a complete literature on graphics recognition, please refer to [7][8][9].

It is our believe that the problem of visual pattern recognition is better solved by borrowing some concepts from the Biological Pattern Recognition **(BPR)** system. We all know that adults and children alike are able to recognize simple 2D visual patterns, such as graphics symbols, with incredible ease and precision. In this regard, one would like to pose the following questions: How does the human's brain recognize a visual pattern? Does it decompose the pattern into its constituents and then uses its knowledge of each constituent to reach the final answer? If this is true, then a child must learn to recognize the geometrical primitives (lines, curves, etc.) before he/she is able to recognize visual patterns such graphics symbol. Evidence from practice proves the contrary. Children are able to perform visual pattern recognition of simple shapes without knowing the names of its primitives. Little is known about the *exact* process by which the human's brain develops a cognitive information learning processing. Nevertheless, evidence from current theories of Visual Cognition and Computational Neuroscience [10] tell us that intensity variations and directions in a 2D visual pattern, e.g. graphics symbol of a resistor, produce neuronal activities and that these activities are built into compact representation and then associated with whatever a word we attribute to the entire pattern. This association is learned with time and stays forever. It is provoked every time similar patterns are presented to the human visual system. Of course and without any doubt, we adults sometimes use some sort of *deep knowledge*, reasoning for example, to build up a rather complex cognitive learning process. This is evident when we perform complex visual pattern recognition task, such as reading cursive words written by writers of different cultural backgrounds and or writing styles. In such a task we use our knowledge of the various shapes that a character might have. In comparison, a child at the early learning stage has limited knowledge and, thus, will have some difficulty in reading cursive words written with different style and or speed.

The above features of the BPR system are the principle characteristics of Computational Neural Networks **(CNNs)**. In addition, CNNs provide a *model-free* approach. They estimate a solution without a mathematical model of how outputs depend on inputs. They learn from examples, and recognize visual patterns that are otherwise difficult to define.

To understand the distinction between the classical and CNNs approaches, let's consider the problem of developing a method for recognizing the graphics symbol of a transistor, for example. On the one hand, if one adopts the classical approach, one would have to develop an algorithm and specify how this algorithm must perform the required task. This might be accomplished by extracting the syntactical constituents (vertical, horizontal and diagonal lines, and arrow) and, thereafter, building a set of grammars to perform the decision. On the other hand, if one adopts the CNNs approach, one needs to select an appropriate topology and then train the network by presenting it with samples of input-output mapping. The network itself extracts the most prominent features from the input patterns, builds these features into a compact representation, and associates this representation with the output pattern. By comparing the two approaches, two differences could be observed. First, in the classical approach one need to impede in the algorithm knowledge of how to recognize the symbol, whereas, in the case of CNNs the knowledge is acquired during training. Second, to recognize a different type of graphics symbol one must, in the case of the classical approach, modify the algorithm and *probably* provide a new set of grammars; and only provide new samples of input-output mapping, in the case of on-line CNNs. The ability of a system to learn from examples and continue learning without forgetting its previously acquired knowledge is important if the system is to operate on-line with little interference from the outside world.

Based on the above, we have developed a NNs-based module for the recognition of the graphic symbols of the electronic components mentioned above. The module is composed of a number of the Fuzzy ARTMAP neural networks that is equal to the number of graphics symbols to be recognized. The reasons for selecting the Fuzzy ARTMAP are its ability to learn from positive examples only [11] and operate autonomously. A detailed discussion of the Fuzzy ARTMAP can be found in [12]. The following two sections present, respectively, the architecture of the proposed model and the experimental results. Conclusions and bibliographical references are given in sections four and five, respectively.

2. Architecture of the Recognition Module

A block diagram of the recognition module is shown in figure 3. It is composed of three stages: pre-processing, normalization and recognition. At the pre-processing stage, a thresholding, based on Otsu's algorithm [13], is applied to the input image. The binary image is then scanned by a window whose size depends on the graphic symbol to be recognized (Refer to figure 2). Each extracted segment is normalized to half of the size of the scanning window and, thereafter, is applied to the recognition stage. As seen from figure 3, the recognition stage is composed of 19 Fuzzy ARTMAP NNs, each of which is responsible for recognizing the 2-D shape of one electronic component *only*. The purpose of such structure is to reduce the complexity of the problem to a manageable level and to allow for a possible expansion in the future to other graphics symbols.

2.1. Normalization

The purpose of the normalization stage is to produce a thinned image whose size is half of that of the scanning window. The Nearest Neighbor [14] and Zhang & Suen [15] algorithms were used, respectively, to perform the thinning and scaling operations. The quality of the reduced, thinned image depends on the sequence by which those two algorithms are performed. As it is seen in figure 4a, the sequence: *scaling-and-then-thinning* produces a good reduce, thinned image, without any line discontinuities; as opposed to the sequence in figure 4b. However, if the gray image is of poor quality, the result of the normalization process will be poor as well (Figure 5a).

To overcome this problem, we have applied a dilation operation on the reduced image prior to the thinning operation (Figure 5b). We have found that, in general, better results can be obtained when the dilation operation is performed right after the thresholding operation (Figure 5c). In the proposed recognition module, we have used the normalization operations shown in figure 5c.

3 Experimental Results

The performance of the proposed recognition module was evaluated by first training each Fuzzy ARTMAP with *segmented images* of the respective electronic component, ***only***. This is based on the One-Class Problem Approach, as mentioned in section 1.1. Variations of the same image were also included in the training set. These variations were found to reduce the search time significantly. The parameters of each Fuzzy ARTMAP were: $\rho = 0.85$, $\beta = 0.6$, and $\alpha = 1.0$. The training iteration and epoch size were, respectively, 1000 and 16.

After training is completed, the Fuzzy ARTMAP-based module was used to search for specific component in a database of circuit layouts. The search process starts by scanning each image of a circuit layout with a window that belongs to the component under search. Each scanned block is then fed into the recognition module. Noise-removal operations were applied, prior to the normalization process, to remove any spots and text that might exist in the scanned image. The search process is continued until the entire image is scanned. It should be noted that to search for a specific component, only one Fuzzy ARTMAP is activated. Performance of the recognition module was measured according to the False Acceptance (**FA**) and False Rejection (**FR**) error criteria. FA and FR indicate, respectively, the umber of negative patterns that are classified as being positive, and, number of positive patterns that are classified as being negative.

The training set was composed of 380 images (20 images/component), and the test set contained 30 images of electronic circuit layouts. The initial results, in terms of FA and FR errors for each Fuzzy ARTMAP, are shown in table 1. The average percentage error, E_t, of the system is 3.73% and is calculated according to the following equation:

$$E_t = \frac{FR + FA}{2(\#\text{of Patterns})} * 100 \qquad (1)$$

4 Conclusions

In this paper we have presented our initial investigation for developing a CNNs-based module for recognizing graphic symbols of electronic components in circuit layouts that are scale-invariant and exist in predefined orientation. The approach was based on some concepts of the BPR system, i.e., recognition by association and without making an explicit decomposition of the graphics symbol. The implementation of such approach was possible with the Fuzzy ARTMAP neural network. As presented above, each Fuzzy ARTMAP was trained to recognize the graphic symbol of one electronic component only. After training has been completed, the recognition module was used to locate graphic symbols, given their names, in a database of 30 images of electronic layouts. During the search process, only one Fuzzy ARTMAP is activated.

As demonstrated in table 1, each Fuzzy ARTMAP performed well with respect to the graphic symbol that was taught to recognize. Most of the errors were due to the existence of text at the proximity of a graphic symbol, which the noise-removal operation failed to clean. Due to the distinct shape characteristics of the graphic symbols, each Fuzzy ARTMAP did not make any negative classification errors.

At this stage, the proposed approach is limited to specific application, i.e., locating graphics symbols that are scale-invariant and exist in predefined orientation. However, the general structure of the module can be adopted to locate graphics symbols of different sizes and orientations.

Despite the promising results obtained in this work, we are aware that further tests and analysis are required with a larger database. In addition, extensive study will be conducted to reduce the FR errors to acceptable values.

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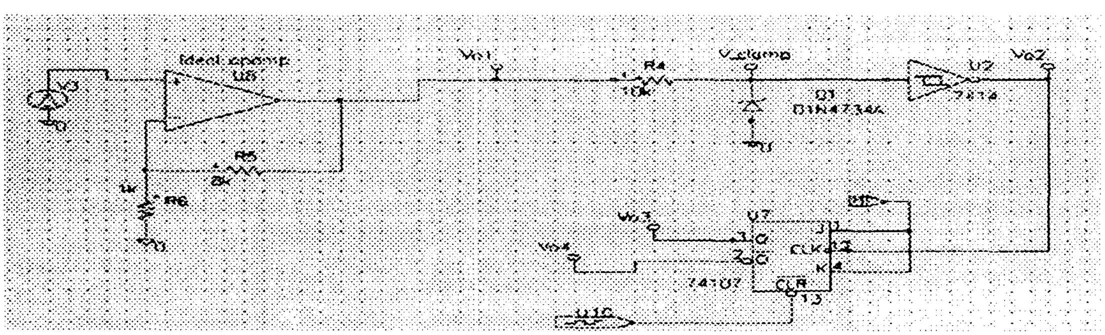

Fig. 1. Examples of electronic circuit layouts (Actual size is reduced to fit in the page).

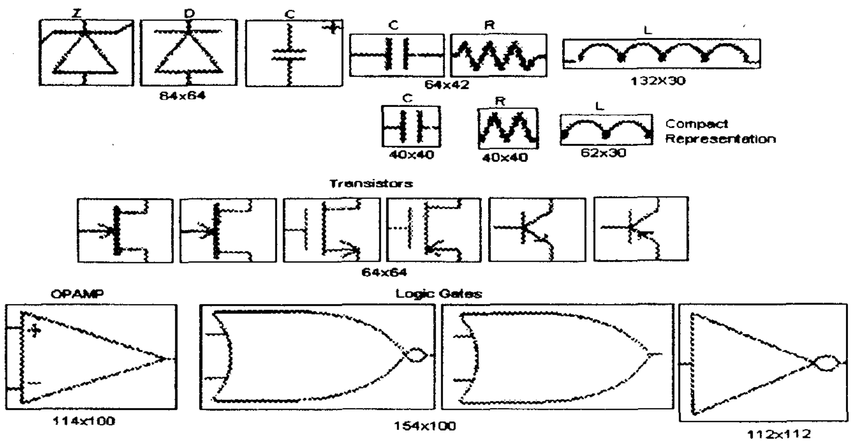

Fig. 2. Example of Graphic symbols of electronic components each of which is fit into its scanning windows. layouts (Actual size is reduced to fit in the page).

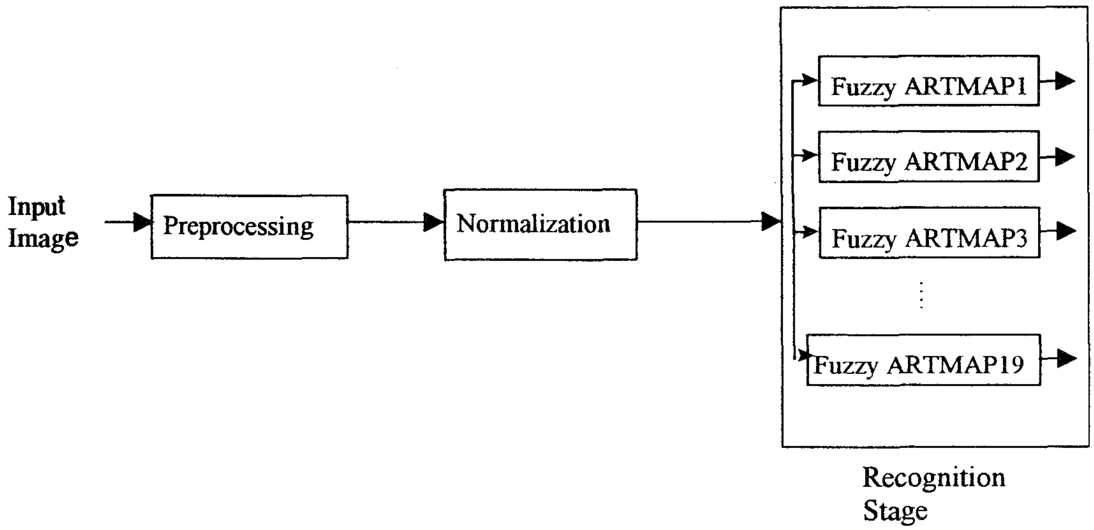

Fig. 3. Block diagram of the Fuzzy ARTMAP-based recognition module

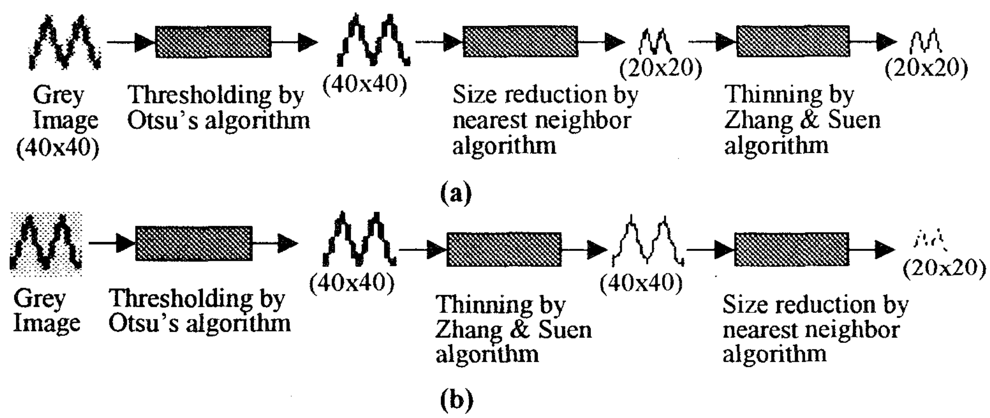

Fig. 4. Two sequences of normalization processes performed on the graphic symbol of a resistor. It can be observed that sequence (a) produces better result than sequence (b), as far as the quality of the output image is concerned. The quality of the reduced, thinned image depends on the se-

quence by which those two algorithms are performed. In figure 5a, the application of the scaling algorithm prior to the thinning one produces good result, without any line discontinuities.

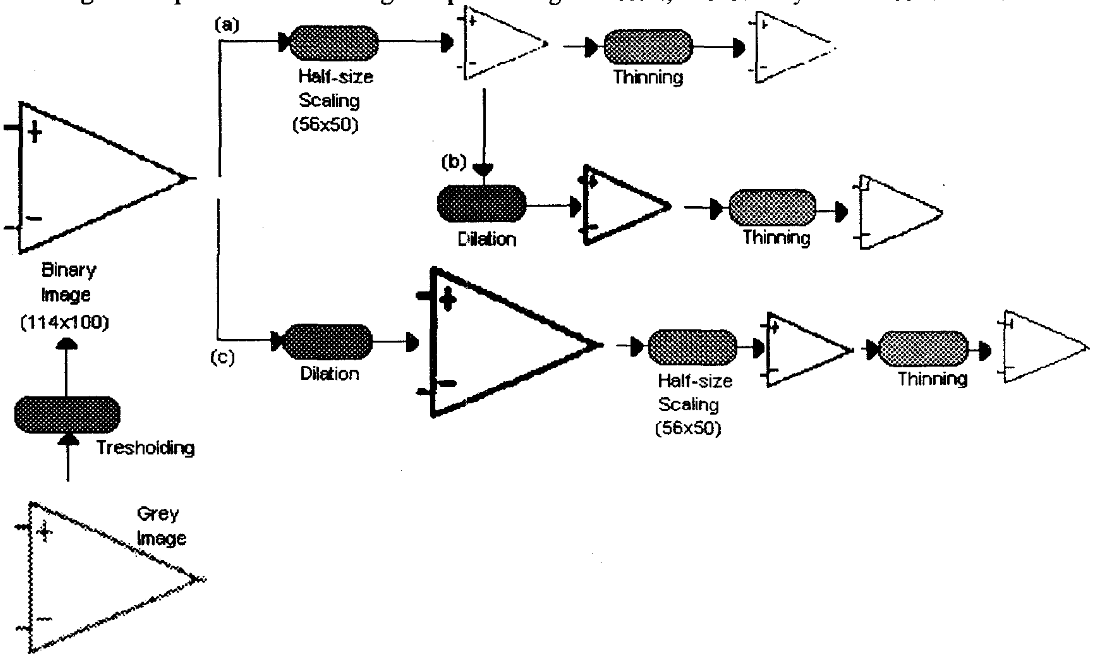

Fig. 5. Three distinct normalization processes performed on the graphic symbol of an OPAMP. a) Same as in Fig. 5. Observe the discontinuity in the thinned image. This is due to the rather poor quality of the input gray image. b) Alternatively, one can improve the quality of the output image by applying a Dilation operation on the reduced image of process (a) and, then, apply the thinning operation. c) A second alternative is to apply the dilation operation on the binary image, prior to the scaling and thinning operations.

Graphic Symbol	# of Patterns	False Rejec.	False Accept.
Resistor	220	20	0
Capacitor1	175	15	0
Capacitor2	205	23	0
Inductor	25	2	0
OPAMP	158	8	0
Transistor1a	178	12	0
Transistor1b	100	7	0
Transistor2a	55	9	0
Transistor2b	46	10	0
Transistor3a	78	6	0
Transistor3b	94	5	0
Diode	68	4	0
Zener	89	3	0
OR	123	5	0
NOR	94	4	0
AND	105	3	0
NAND	57	3	0
NOT	88	6	0
XOR	93	8	0
Total	2051	153	0

Table 1. Evaluation results of the proposed recognition module.