Efficiency and Accuracy Analysis of a Fuzzy Single-Stroke Character Recognizer with Various Rectangle Fuzzy Grids

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Nowadays the market share of portable computer devices is continuously growing. In some cases the use of physical keyboards in portable devices is not possible at all. This is why designers are in need of new methods for data input, such as software-based virtual keyboards combined with touch interfaces, further voice and handwriting recognition.

Processing written text by computers nevertheless has a long history. In this field there are still many ongoing research and development projects aiming to achieve the more accurate recognition of handwriting. In her study LaLomia [1] determined 97% as the general user acceptance rate for handwriting recognizers.

In this paper the results of a study on the efficiency and accuracy of a fuzzy logic-based [2] single-stroke character recognizer are presented by using various rectangle fuzzy grid cells in the feature extraction phase.

During the design of the recognition algorithm limiting the resources needed for the method was targeted as a primary goal besides the acceptable recognition accuracy. A solution has been worked out to eliminate geometrical transformations from the method so we could reduce the overall computational complexity. In the early stage of the development we decided to handle the stroke segmentation as a separate problem so we could focus on the concept of the recognition engine.

Each stroke could be represented as a continuous function sampled by the digitizer tablet. The system collects all the coordinates in chronological order representing the pen movement. Due to hardware bottlenecks the input device is not capable of collecting all parts of the signal and the distance between the sampled points may differ.

During the pre-processing phase the input stroke is re-sampled. The first and last points of the stroke are stored for reference. After that, the filtering algorithm calculates the distance between the points. If the distance reaches the minimum threshold, the point will be added to the re-sampled stroke if however it is not it will be filtered out.

Input signals are identified by the width/height ratio of the stroke and the average number of stroke-points in the rows and columns of the grid. Our tests pointed out a big disadvantage of crisp grids (grids with sharp borders). If the angular offset of the input stroke and the etalon symbol are different then the distribution of the points in the grid will also differ. This might cause a high reduction in recognition rates. As a solution we designed a grid with blurred boundaries which will be referred to as fuzzy grid (inspired by fuzzy logic).

The symbol set is a modified version of Palm's Graffiti single-stroke alphabet and it contains 26 different symbols. The rule base was determined by a subset of the collected samples. The extracted stroke-features are used as input parameters for the fuzzy rules [3, 4]. The number of rules is equivalent to the number of the symbols in the base set. The consequent part of the rules represents the degree of matching of the parameters of the input stroke and of the parameters of the symbol represented by the given rules. The best fitting rule will be chosen as the output of the inference.

Our first implemented system [5] used a four-by-four fuzzy grid and reached 94.3% accuracy. Our more recent work compared the efficiency of the system with different N-by-N (square) fuzzy grids using trapezoidal membership functions of rows and columns defined to cover each point constituting Ruspini-partitions [6]. As a result 99.4% recognition rate was achieved with the 6-by-6 fuzzy grid. In this work different numbers of rows and columns were analyzed for the N-by-M fuzzy grids in order to find its optimal size. The new system achieved 99.2% recognition rate with a 6-by-4 fuzzy grid which almost reached the best accuracy of the square fuzzy grid, however it resulted in a decreased computational complexity.

To make the system more accurate the algorithm includes a training phase where the specific features of the user's handwriting is learned but this function was disabled during the tests to avoid its effects on the accuracy. In the adaptation phase an evolutionary algorithm [7] was used due to the limited available hardware resources. The results clearly showed that bacterial evolutionary algorithms [8, 9] were suitable for tuning fuzzy sets. During the adaptation the system had to consider the features of the previously stored samples as much as the new input stroke. All parameters of the new symbol had to fit to the tuned fuzzy set of the target symbol as much as possible without decreasing the fitness of the stored samples. At the same time the method had to minimize the overlap of the target and non-target fuzzy rules without modifying the fitness of the samples stored in non-target symbol classes. Classical evolutionary solutions could not be used due to the special constraints in which the different dynamic fitness functions had to be deployed for the different symbols at the same process. Without these constraints the fuzzy sets would overlap in the different rules which would decrease the recognition rate. The bacterial evolutionary algorithm has been extended with "punish" and "reward" option. The modified algorithm solved the overlap-problem and resulted in an increased average recognition rate.

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