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# An Analysis of Mathematical Expression Recognition Techniques

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*Abstract :*The field of mathematics is very important with its applications in every aspect of science in general and engineering in particular. Mathematical expressions form a vital component of mathematical literature. Consequently, recognition of mathematical expressions has become a highly active and challenging research area nowadays having great practical significance. Different concepts from pattern recognition and digital image processing are utilised for the accomplishment of classification and recognition of mathematical expressions. The main task involved is the automatic recognition of different mathematical symbols. Several classification approaches have been used on different databases under different experimental conditions resulting in different performances and classification accuracies. In this paper, a review of different techniques of mathematical expression recognition is presented.

***Keywords:*** ANN, HOG (Histogram of Oriented Gradients); KNN; math recognition system; SVM, segmentation; WNN

## I. INTRODUCTION

The remarkable increase of internet has created an evolving tendency of distributing information through this distributed information network. This has led to some new concerns that can be managed and solved through some new enquiries and investigations like digital library and distance learning. These concepts can be turned into reality by investing into some effective procedures for conversion of the document or paper based records into electronic form that can be managed by the digital computers and transferred through the internet.

Being an important part of the scientific and engineering literature, the classification and recognition of the mathematical expressions has become an exciting and stimulating research area of the pattern recognition with unlimited real-world implications. Mathematical expression recognition can be accomplished in terms of two main sub-steps: (i) symbol recognition and (ii) structural analysis of the mathematical expression (ME) [1]. As symbol recognition has performed very well by reaching high accuracy results [2], the core focus of the current research efforts is on the analysis of structural aspect of the MEs. Significant number of researchers have and are continuously trying to resolve the problem of recognizing a mathematical expression (ME) [3] [4]. Although many systems have achieved a notable performance; there is still lack of a unified technique in this domain to assess their performances. Also, if viewed globally, there is a limit for the comparison of results obtained from different systems for many reasons.

### *A. Mathematical Expression (ME) Specifications*

A mathematical expression (ME) is a two dimensional design of math symbols. A symbol comprises a group of black pixels in case of offline ME recognition while in case of online ME recognition, a math symbol consists of one or more strokes. A stroke can be defined as the sequence of points between a pen down and a pen lift. Thus, recognition of a mathematical expression consists in finding the best possible grouping of the strokes in online recognition or pixels (in offline recognition) to represent symbols. Moreover, spatial relations among symbols must be determined in order to find out the layout of the recognized expression. Most of the recognition systems developed so far consider the recognition of ME as a set of three sub stages [5]: segmentation, recognition and structural analysis and interpretation. The segmentation step deals with the grouping of strokes or pixels belonging to the same symbol. The symbol recognition step associates a label to each of the determined symbols. Then, the phase of structural analysis evaluates different relationships between the symbols and uses syntax to suggest an effective interpretation of the ME.

### *B. Challenges and Ambiguities of Mathematical Expression (ME)*

Mathematical expressions are an important part in most of the scientific and engineering disciplines. But there are so many challenges residing in the recognition of mathematical symbols or expressions and in their evaluation. Some of the main challenges are discussed as follows:

- The inputting of mathematical expressions into a computer is much more difficult as compared to that of plain text. This is so because the mathematical expression comprises a variety of special symbols (over 2000), operators, digits, the letters of English alphabet and a number of special letters of Latin/ Greek/ Arabic literature [6].
- The diverse pool of characters and symbols demands the traditional keyboard to be altered and redesigned to adjust all the keys needed. Another approach would be to utilise some of the special keys in the keyboard like function keys together with some distinctive key arrangements to signify the special mathematical symbols [7]. Defining a special keyword set for the representation of distinct mathematical characters and symbols would be another desired approach [8]. However, rigorous exercise and training is required to work with such specially designed keyboards or keywords. Alternatively, mathematical expressions could be simply written on an electronic tablet by making use of pen-based computing

technologies so that the computer can recognize them automatically. Now if the expressions are already in the form of printed documents, it needs to be scanned. Then only computer would be able to recognize the expressions directly from an image.

- The non-availability of an open public dataset of online or offline handwritten mathematical expressions (MEs) is another major challenge [5]. It forces the researchers to collect and develop the set of mathematical expressions (MEs) on their own that has a tendency of being limited to a subset of expressions or to certain domains. Thus a direct comparison of performance of different systems is not possible. Moreover, each system develops and implements its own data structure to represent ground truth of mathematical expressions (MEs). No common measures of evaluation are available for the same.
- In case of handwritten mathematical expression, recognition gets more difficult as there would be distinctions in the size of symbol and its font type [9]. Moreover, there would be variations in the writing styles from person to person and the image quality as well offering a great challenge to the math recognition system.
- Mathematics uses many analogous symbols with lesser variations with different notations conveying meaning through indirect use of spatial relationships among symbols and it is highly complicated to capture all such relationships [2].
- In classic mathematics, different styles of the same letters can have entirely different senses [10]. The difficulty is most critical in pure mathematics and not in engineering. For example, within a single article in p-adic representation theory, the bold letter G often will represent a group over an algebraically closed field, the plain italic G will represent its rational points over a p-adic field *k*, and sans-serif G a reductive quotient over the residual field _*k*, with German g used for a Lie algebra.
- The language producing MEs is not a totally formal language. The same expression can be understood differently in different circumstances [5]. For example, the expression $f\ (m+1)$ can have two different interpretations: it can be deliberated as the variable $f$ multiplied by the expression ($m+1$); or the function $f$ applied to the value $m+1$.
- Finally, there is not a formal definition of mathematics notation and many dialects are in use [11]. Mathematical symbols are invented or redefined as and when needed by the users of the notation just like the natural languages. So these characteristics act as the major challenges in the definition of reliable, robust and efficient methods for segmentation and recognition of the symbols in the mathematical expressions.

### *C. Mathematical Expression (ME) Representation*

An important query is to know what to represent in the ground truth of an ME. Is it the plan of the set of symbols or is it the understanding of the expression? Usually, the ultimate outcome of a recognition process is a LaTeX string, or a MathML structure [5]. A LaTeX string is a very common depiction of a ME but it is associated with some limitations. First, it just signifies the design of the expression, and does not propose to interpret the mathematical expression. Second, this depiction is not distinctive as the same design can be described with some alternatives. On the other hand, MathML [12] is an evolving XML format planned to draw ME in convenient documents like portable web pages. Moreover, it intends at encoding either mathematical design or mathematical meaning (for graphical displays; input for computer algebra systems; plain text displays; print media). In the first case, a given explanation should define a single layout, while in the second case; the ME will be presented differently by different renders. Thus it becomes clear that MEs must not be ground truthed only by their content but notable with their presented symbols and their design. However, in progressive steps of ME recognition it is possible to apply some alterations in order to acquire the content if needed with the problems related to ME uncertainties discussed in the previous section. On the other hand, the recognition systems have their own ME representation depending on how they accomplish their recognition. Many systems make trees to represent expressions as a result of structural and syntactic analysis. Hence, these trees hold more information about the construction of the expression. Naturally, trees are very beneficial to assess recognition systems because they cover not only spatial and logical relations between symbols, but also the symbols recognition and segmentation information.

In [13], the authors streamline the use of trees as structure presentation. They present hidden writing area (HWA) related to each input stroke that defines the relation with previous one.

A more common way to represent the structure of an expression is to use relational trees. Binary trees were used in [14]; where non-terminals are the possible logical relations between symbols, and terminals are the recognized symbols.

More recently, [15] re-adopt the use of symbol relation trees (SRT). An SRT is formed with a dominant symbol and then its sub-expressions as child nodes. The spatial relationship between a dominant symbol and its children is coded using the edges. Then each sub-expression is denoted recursively by a SRT using a new dominant symbol. Spatial relations are chosen among six possible types: inside, over, under, superscript, subscript and right.

Another approach is offered in [16] in order to construct a syntactic and semantic free representation, the authors use a baseline structure trees (BST) that signifies the hierarchical structure baselines in an expression.

### *D. Types of Input to a Mathematical Expression (ME)*

The input mathematical expressions to a math recognition algorithm can be present in three different forms [2]:

i) Vector Graphics (such as PDF) [17] [18],
ii) Strokes (such as pen strokes on a digital data tablet)
iii) Simple Document Image

The form of the input greatly decides the procedure that is required for extraction of expressions and the recognition of different constituent symbols and characters. For example, there is no requirement of implementing segmentation for symbol extraction or optical character recognition in case of a PDF document as encoded symbols are directly provided here. Based on these different input forms, the recognition can be off-line or on-line [1].

- Off-line recognition provides a static representation of the data where either printed or handwritten expressions are given in the form of images or bit-maps.
- Conversely, on-line recognition provides a dynamic representation of data when expressions are created by digital computers with pen devices (data tablets, contact sensitive whiteboards) that use digital ink for storing and recording of the data.

### *E. Problems Associated with Math Recognition System*

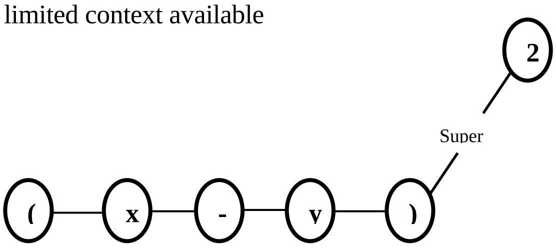
The following four key problems arise in the recognition of math symbols (see Figure 1) [4]:

i) *Expression Detection*: Expressions must be first identified and segmented. Methods for detecting offset expressions are fairly robust, but the detection of expressions embedded in text lines remains a challenge.

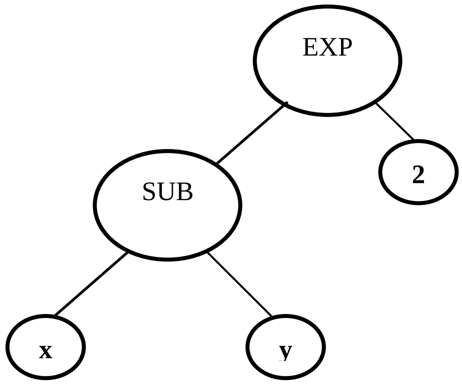
ii) *Symbol Extraction or Symbol Recognition:* In vector-based representations, such as PDF, symbol locations and labels can be recovered, though some handling of special cases is needed. In raster image data and pen strokes, detecting symbol location and identity is challenging. There are hundreds of alphanumeric and mathematical symbols used; many so similar in appearance that some use of context is necessary for disambiguation (e.g. O, o, 0).

iii) *Layout Analysis*: Analysis of the spatial relationships between symbols is challenging. Spatial structure is often represented using a tree, which is termed as symbol layout tree. Symbol layout trees (Figure 1a) represent information similar to LATEX math expressions; they indicate which groups of horizontally adjacent symbols share a baseline (writing line), along with subscript/superscript, above/below, and containment relationships. Symbols may be merged into tokens, in order to simplify later processing (e.g. function names and numeric constants).

iv) *Mathematical Content Interpretation*: Symbol layout is interpreted, mapping symbols and their layout in order to recover the variables, constants, operands and relations represented in an expression, and their mathematical syntax and semantics. This analysis produces a syntax tree for an expression known as an operator tree (Figure 1b).Given definitions for symbols and operations in an operator tree, the tree may be used to evaluate an expression, e.g. after mapping the tree to an expression in a CAS language such as Matlab, Maple, or Mathematica. However, determining the correct mapping for symbols and structures can be difficult, particularly if there is limited context available




(a) Symbol layout tree




(b) Operator tree

Figure 1: Symbol layout tree and operator tree for $(x-y)^2$

### *F. A Simple ME Recognition System*

A general system overview for mathematical expression recognition is shown in Figure 2 [19]. The first and foremost step is data acquisition. Next step is pre-processing in which image cleaning takes place and the image is converted to a form that is suitable for further processing like size normalization, binarization, skeletonization and noise removal commands and algorithms are implemented. Then the pre-processed image is supplied to segmentation and feature extraction steps. The expression is segmented into sub components and each character is separated. The principle of the connected component labeling can be used to group under a unique label all adjacent pixels in an image in order to distinguish and extract different disconnected structures. This means that all pixels in a connected component share similar pixel intensity values. Then the feature set which is useful for training and recognition of the system is extracted. Different techniques of feature extraction can be used like Projection Histograms, HOG (Histogram of Oriented Gradients) feature extraction, Zoning of structural features, etc. Each extracted symbol is placed in the appropriate class to which it belongs by using a proper classification algorithm. Different algorithms available include Support Vector Machine (SVM), Artificial Neural Network, Hidden Markov Model and Fuzzy Logic. Training and testing of the classifier are applied in the recognition step.

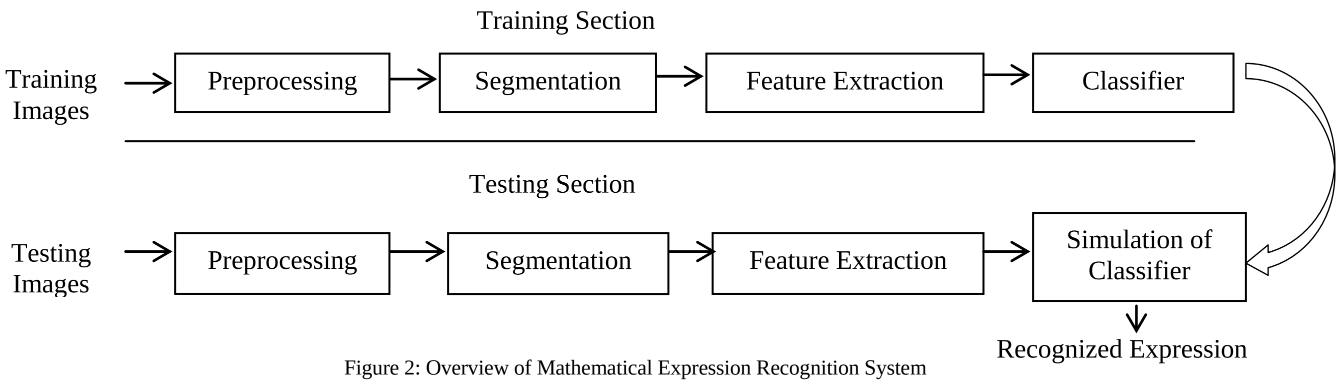



Figure 2: Overview of Mathematical Expression Recognition System

## II. LITERATURE SURVEY

Since 1950, the recognition of mathematical expressions has been popular research area. Substantial amount of literature is available where researchers have used different concepts and techniques of digital image processing, artificial intelligence and pattern recognition. The field has been so challenging because of the ambiguities and challenges inherent in the mathematical expressions Almost all researchers have faced one or the other challenge while developing and evaluating the math recognition systems. Different classification accuracies and recognition results have been achieved by implementing different approaches of feature extraction and classification. For classification the main approaches being used include HMM, WNN technique, SVM classifier, ANN, Multilayer Perceptron Model and the Fuzzy approach. A brief review of some important research works in this field is presented here.

Ahmad Montaser Awal et al [5] used Multi-layer Perceptron Model and a dataset comprising 839 symbols claiming an accuracy of 87.5% and also, discussed some issues related to the problem of ME (Mathematical Expression) recognition. The first and foremost issue is the definition of how to ground truth a dataset of handwritten mathematical expressions, and the other important issue is that of benchmarking systems. As the field of handwritten mathematical expression recognition has been performing very well and is of vital importance, this paper concludes that it is the need of hour to standardize different evaluation measures and develop public benchmarking so as to specify the achievements of different systems.

Harold Mouchere et al [20] reported on the third international Competition on Handwritten Mathematical Expression Recognition (CROHME), in which eight teams from academia and industry took part. The training dataset used here includes more than 8000 expressions, and new tools and novel techniques were developed for evaluation of the performance at the level of strokes as well as expressions and symbols.

Kang Kim et al [21] presented a rule-based approach that utilizes some types of contextual information to improve the accuracy of handwritten ME recognition. A layered structure search forms the basis of this system. A recognition accuracy of 87.7% is reported in symbol labeling including segmentation and structuring, and 38.7% in mathematical expression level for KME-I database. Kim used contextual rules of symbols to improve the accuracy of mathematical expression recognition to 77%.

Sanjay S. Gharde et al [22] discussed various steps of recognition process for simple mathematical equations. The paper describes the steps of pre-processing, segmentation, feature extraction, classification and recognition for mathematical symbol as well as for simple expression. The overall accuracy of the recognition system is affected by feature extraction and classification methods used among all the different phases involved in it. The feature extraction methods used are Zoning, Skeleton based direction and Projection Histogram. ANN and SVM classifiers are used for recognition, resulting in 87.5%, 98.5% recognition accuracy, respectively. Thus it is concluded from this paper that SVM classifier is better among the used ones.

Stephen M. Watt et al [23] propose a recognition system that offers a component of a handwritten interface for computer algebra systems such as Maple. A pre-classification strategy together with elastic matching, a method that implicates computation proportional to the set of candidate models, is implemented for improving the recognition speed. This is achieved by pruning the prototypes after examining character features. When these features are incorporated into elastic recognition system, a substantial improvement in the recognition speed is achieved maintaining a high accuracy of recognition as well.

Xue-Dong Tian et al [24] presented projective features and connected components' labeling method to segment the symbols in expressions. Then the peripheral features and directional line element features are extracted from symbols. Finally, a coarse-to-fine classification strategy is employed to recognize symbols with these features. Experiments are carried out that confirm that the proposed methods can achieve acceptable recognition accuracy with a good speed. Mathematical documents scanned in 600dpi are used to perform experiments in recognition. Recognition rates of 98.22% and 96.94% are achieved for math handbook and math journals symbols, respectively with 97.81% being the overall correct recognition rate. Touching symbols, broken symbols and symbol similarities are the main sources of error in experimental results.

Preeti Niranjan et al [25] made use of SVM (Support Vector Machine) along with morphological operations in recognizing hand gestures for a natural HCI system. The concepts of Vision based gesture recognition system are used in understanding the hand gestures for making a virtual touch screen of numbers. The virtual touch screen then shall be used for computing simple mathematical operations. Image classification of gestures is done using State Vector machine.

Christopher Malon et al [10] explored the use of unsupervised classifier, SVM to enhance and improve the classification of InftyReader, a free system for the OCR of mathematical documents. First, the performance of SVM kernels is compared with the feature definitions on such pairs of letters which usually act as a source of confusion for the InftyReader. Secondly, an efficient technique is described that is capable enough to perform multi-class classification with SVM, making use of the ranking of options and choices inside the confusion clusters of InftyReader. The complexity is low and the addition of the proposed technique in InftyReader leads to reduction of misrecognition rate by 41%.

Surendra P. Ramteke et al [19] used the properties of connected components to calculate centroid and bounding box which act as the main features extracted from each character. The system proposed in this paper is accomplished using the approach of neural network for the recognition of expressions as well as the symbols. The recognition rate achieved is around 90%.

M. Hanmandlu et al [26] present the recognition of Handwritten Hindi Numerals based on the modified exponential membership function fitted to the fuzzy sets derived from normalized distance features obtained using the Box approach. Two structural parameters, derived by the optimization of the criterion function used in input fuzzy modelling, are used for the modification of the exponential membership. Then reinforcement learning is incorporated by reviewing the past error values of the criteria functions for employing a ‘Reuse Policy’. In training, a 25- fold improvement is achieved by carrying out the experimentation of reinforcement learning (‘Reuse Policy’) on a limited database comprising almost 3500 Hindi numeral samples with 95% overall recognition rate.

Anh Duc et al [27] propose a model for recognition of online handwritten MEs, to solve all the local uncertainties in symbol segmentation as well as recognition and for enhancement of the structural analysis. MEs are represented in CFGs (Context Free Grammars) and for analysis of their 2d structure; the CYK (Cocke-Younger-Kasami) algorithm is used. Moreover, two SVM models are used for developing a method to learn structural relations from training patterns for improving recognition rate. Stroke order is used to reduce the complexity of parsing algorithm. The whole algorithm is evaluated in the CROHME 2013 database for showing the improvement in recognition rate and processing rate.

Scott MacLean et al [28] have used relational grammars and fuzzy sets for introducing a new fast and incremental algorithm for parsing 2D input. A fuzzy set is used to represent the parses in the input where their comparison with the handwritten input is measured by the membership functions of the parses. Some prevalent approaches such as rectangular partitions and shared parse forests together with some new concepts like relational classes and interchangeability are used to identify and report parses in an efficient manner. A correction mechanism is proposed as well that allows the users to examine all the parse results so as to choose the genuine interpretation in case of any ambiguity like recognition errors. These corrections are then integrated into subsequent incremental recognition results. Finally, two empirical evaluations of the recognizer are included with one of them using a new user-oriented correction count metric and the other one replicating the CROHME 2011 math recognition contest.

F. Alvaro and J. A. Sanchez [6] have tested and compared different classical and novel classification techniques for mathematical recognition and classification on same database and in same experimental conditions. Four different classification techniques have been considered in this paper which include k-nearest neighbour (KNN) rule, SVM classifier, Weighted Nearest Neighbour (WNN) Technique and Hidden Markov Model (HMM). This research concluded SVM and WNN are the best ones as the experimentation on similar databases showed the best results for them. HMM showed the worst results among all the four techniques when used for handwritten text recognition.

F. Simistira et.al [29] presented a great contribution in solving the difficulties associated with structural analysis of mathematical expressions. This is made possible by extracting appropriate feature vectors to characterize the spatial affinity of the possible objects in a mathematical expression (mathematical symbols or sub-expressions) that is being examined or observed and by using two known techniques of machine learning for classification: (i) Support Vector Machines (SVM) and (ii) Artificial Neural Networks (ANN). These techniques help in distinguishing the spatial relations between the constituents of a mathematical expression. The two classification strategies are implemented and evaluated on two marked datasets of spatial relations: - (i) mathematical expressions obtained from the CROHME-2012 dataset (ii) and publicly accessible dataset of MEs having marked spatial relations. From this paper, it is concluded that by incorporating an additional feature to the SVM classifier, there is a reduction in the error rate from 3.20% to 2.87% when implemented on MathBrush dataset. However, the error rate reduces from 4.09% to 3.35% in case of Artificial Neural Network classifier when implemented on the same dataset under similar conditions, which is still more than that of SVM classifier. This difference is due to the use of just one hidden layer in the proposed ANN and so it is expected to lead to a lower error rate if more hidden layers are introduced. Recognition of spatial relations between isolated mathematical symbols and sub-expressions has major limitations and drawbacks that may be due to the lack of information about the whole leading to imperfect recognition results. It concludes that more efficient methods need to be explored that would allow the context of evaluated mathematical symbols or sub-expressions to be used for enhancing the overall performance of recognition.

## III. CONCLUSION

In this paper, we have discussed the preliminaries of mathematical expression recognition. It is concluded that there are many challenges associated with ME recognition that make it a challenging and daunting task. A brief survey of related research works carried out by different researchers has been presented here. It is observed that different classification techniques perform differently under different experimental conditions on different datasets. The concepts of pattern recognition and digital image processing need to be further examined, implemented, and evaluated to provide better procedures and algorithms for ME recognition.

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