Musical Document Retrieval through Image Spotting

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ABSTRACT

In this paper, we present a novel approach for retrieval of handwritten musical documents using a query sequence/word of musical scores. In our algorithm, the musical score-words are described as sequences of symbols generated from a universal codebook vocabulary of musical scores. Staff lines are removed first from musical documents using structural analysis of staff lines and their connection with symbols. Symbol codebook vocabulary is created in offline by a feature extraction and unsupervised classification method. Next, using this symbol codebook the music symbol information in the document images is encoded. Given a query sequence of musical symbols in a musical score-line, the symbols in the query are searched. Finally, an approximate string matching based sub-string matching algorithm is applied to find query words. For codebook, three different feature extraction methods namely: Zernike Moments, 400 dimensional gradient feature and Profile features are tested and three unsupervised classifiers using SOM, K-Mean and Dynamic Time Warping are evaluated in our algorithms. The proposed method is tested on a collection of handwritten musical documents from a public dataset. The performance results are compared with different codebook vocabulary learning methods.

**Keywords**

Musical Document Retrieval, Staff Removal, Symbol Classification, Approximate String Matching.

# 1. Introduction

Graphics Recognition (GR) has become popular in applications such as Optical Music Recognition (OMR), Engineering Drawing, Maps etc. The main goal is to interpret the graphical documents by recognizing graphical parts and symbols within it. Later, the document contents can be used for efficient indexing according to the interest of the user. With the rapid progress of research in document image analysis and understanding many applications are coming up to manage the paper documents in electronic form to facilitate indexing, viewing, extracting the intended portions etc. Research in

Recently, many works have been done in the analysis of handwritten music scores in context of OMR. The focuses of the research are mainly recognition of handwritten music scores, and the identiﬁcation (or veriﬁcation) of the writer of an anonymous music score [6]. Browsing musical document collection by content information will undoubtedly enhance the user interest for searching their particular interests. Musical scores could be useful and important information that could be used as key for searching and indexing of handwritten musical documents. The main challenging task is due to complexity of handwriting, symbol touching with staff lines, etc. The segmentation and recognition of old handwritten music scores is extremely difficult, not only because of the recognition of hand-drawn symbols, but also because of paper aging and degradation. Due to the difficulties in the automatic recognition of hand-drawn music symbols, only the staff removal, writer identification and graphical primitive analysis have been performed. The next steps, mainly object recognition, indexing, are still not implemented.

Many research works have been done for staff removal algorithms, since a good detection and removal of the staff lines will allow the correct isolation and segmentation of the musical symbols, and consequently, will ease the correct recognition and classiﬁcation of the music symbols [3, 4]. Roach and Tatem used a labeling scheme based on the angle information and pixel adjacency to identify these stafﬂine pixels [5]. This extracts a number of “horizontal line pixels”, some of which belong to music symbols. To avoid the removal of symbol pixels on the stafﬂines, some horizontal line pixels are iteratively relabeled as non-horizontal pixels, depending on the labels of their neighboring pixels. Eventually all remaining horizontal pixels are removed. Dalitz et al [4] have presented a quantitative comparison of different algorithms for the removal of staff-lines from music images. It contains a survey of previously proposed algorithms and suggests a new skeletonization based approach.



**Figure 1: Examples of a musical score is shown.**

In fact, the approach [4] does not only perform a musicological analysis of the composition (melody, harmony, rhythm, etc), but also analyzes the handwriting style of the manuscript. In this sense, writer identiﬁcation can be performed by analyzing the shape of the hand-drawn music symbols (e.g. music notes, clefs, accidentals, rests, etc), because it has been shown that the author’s handwriting style that characterizes a piece of text is also present in a graphic document.

In this paper we propose a novel method for retrieval of a musical score, which can help in searching or indexing in handwritten or printed historical documents. In our algorithm, the musical score-words are described as sequences of symbols generated from a universal codebook vocabulary of musical scores. Staff lines are removed first from musical documents using structural analysis of staff lines and their connection with symbols. Symbol codebook vocabulary is created in offline by a feature extraction and unsupervised classification method. Next, using this symbol codebook the music symbol information in the document images is encoded. Given a query sequence of musical symbols in a musical score-line, the symbols in the query are searched. Finally, an approximate string matching based sub-string matching algorithm is applied to find query words. The best matching classes are selected from system to create a cost matrix to perform the matching. Then the cost matrix is used to find the best match of query sequence in the text sequence.

**Figure 2: Examples of staff-line removal in a musical document.**

The main contribution of this paper is to use of dynamic codebook of handwritten music symbols and to generate hypothesis of the music score word location based on the spatial arrangement of these symbols. This approach is robust to detect music score word in noisy, handwritten document environment. The rest of the paper is organized as follows. In Section 2, we explain the preprocessing and symbol extraction procedure. In Section 3, we describe the feature and classifiers used for codebook creation. Section 4 details the retrieval process of query music scores. The experimental results are presented in Section 5. Finally conclusion is given in Section 6.

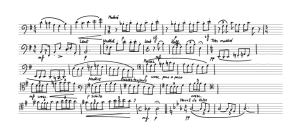
# 2. Preprocessing and Symbol Extraction

**2.1 Staff Line Removal**

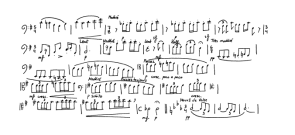
In the literature, almost every paper on OMR deals with the problem and suggests a speciﬁc staff removal algorithm [8]. We have used a simple algorithm proposed by [1] for efficient staff line removal from musical documents. The detail of this method is mentioned here in brief.

The music document image is first thinned by skeletonization algorithm. Next, analyzing the thinned image, the thinned line portions are categorized in two groups: (a) straight staff lines and (b) other non-straight or curved staff-lines. Straight lines (part of staff lines) are further divided into horizontal staff lines and non-horizontal straight lines. Next, staff lines are detected based on the characteristics of each group. The staff line detection method can be considered as passing a ring on a wire (here wire can be considered as staff-line). If there is any obstacle like music score the obstacle portions is retained or deleted based on some measures. For this purpose, staff line height, staff space height, vertical positional variance of the pixels of thinned lines, etc. are computed and these parameters guide the system to detect the staff line part efficiently.

(a)



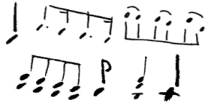
(b)



**Figure 3: Examples of staff-line removal in a musical document. (a) A document with staff-lines. (b) Result of staff-line removal**

**2.2 Symbol Extraction**

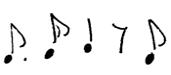
The musical score lines may contain spurious noise points, irregularities on the boundary of the symbols, etc. leading to undesired effects on the system. Background noises are filtered out based on their aspect ratio and pixel density. A major problem of symbol extraction in handwritten documents occurs when the symbols are broken. Some examples of broken symbols are shown in Fig.5.



**Figure 5: Examples of some broken symbols are shown.**

Since, the space between symbols in a musical document is usually much more than that in text document. We have used mathematical morphological operation for joining the broken component. Dilation is used to join the broken parts that are very near.

To obtain the musical symbols, we apply next a connected component labeling to each musical line image and extract individual components. As a result, the musical scores comprising multiple components will also be segmented into different parts. These components are grouped together by checking their overlapping position horizontally. Two components are grouped together, if one is completely overlapped by the other component or they are overlapped partially by overlapping ratio of Tr. Tr is set to 0.8 according to experiment data. Overlapped components are grouped into a single component. Some musical documents contain vertical straight lines (see Fig.1). These vertical lines are filtered out next by checking the aspect ratio.



**(a)**



**(b)**

**Figure 7: (a) Musical symbols and their segmentation result shown in (b).**

# 3 Musical Score Codebook Vocabulary

A dynamic codebook is created in our system for music score word indexing. Different musical symbols can be represented by a small number of visual components. The representatives are learnt through an unsupervised clustering algorithm of all symbols involved in training.

## 3.1 Feature Extraction

To take care of scaling effect, in our system two scale invariant features are chosen: Zernike feature and 400-dimensional feature. These features are used to classify the segmented symbols in our approach.

## 3.1.1 Zernike Moment Feature

Zernike moments are based on a set of complex polynomials that form a complete orthogonal set over the interior of the unit circle [9]. They are defined to be the projection of the image function on these orthogonal basis functions. The basis functions *Vn*,*m*(*x*,*y*) are given by:

 (1)

where n is a non-negative integer, m is non-zero integer subject to the constraints n-|m| is even and, ρ is the length of the vector from origin to, θ is the angle between vector ρ and the x-axis in a counter clockwise direction and *Rn*,*m*(ρ) is the Zernike radial polynomial. The Zernike radial polynomials, *Rn*,*m*(ρ),are defined as:



Note that, *Rn*,*m*(ρ) = *Rn*, −*m*(ρ). The basis functions in equation 1 are orthogonal thus satisfy,



where 

The Zernike moment of order n with repetition m for a digital image function *f*(*x*,*y*) is given by  where  is the complex conjugate of  .

To compute the Zernike moments of a given image, the image center of mass is taken to be the origin. In our approach, the symbols are normalized into 41\*41 before applying Zernike feature computation. The size is considered from the performance of experimental data.

## 3.1.2 400-dimensional feature

The gray-scale local-orientation histogram of the component is used for 400 dimensional feature extractions [10]. To obtain 400 dimensional features we apply the following steps. At first, size normalization of the input binary image is done. Here we normalize the image into 126 x 126 pixels. The input binary image is then converted into a gray-scale image by applying a 2 x 2 mean filtering 5 times. The gray-scale image is normalized next so that the mean gray scale becomes zero with maximum value 1. Next, the normalized image is segmented into 9 x 9 blocks.

A robust filter is then applied on the image to obtain gradient image. The arc tangent of the gradient (strength of gradient) is quantized into 16 directions (an interval of 22.5) and the strength of the gradient is accumulated with each of the quantized direction. By strength of Gradient (f(x, y)) we mean and by direction of gradient , we mean , here , and *g(x, y)* is a gray scale value at an (x, y) point. Next, histograms of the values of 16 quantized directions are computed in each of 9 x 9 blocks. Finally, 9 x 9 blocks are down sampled into 5 x 5 by a Gaussian filter. Thus, we get 5 x 5 x 16 = 400 dimensional feature.



## 3.1.3 Profile feature

The profile features [11] which are described in this section are single-valued, i.e. one scalar value is calculated per column in the original image. Comparability of the feature values across multiple words is ensured by normalizing the feature range to [0, 1].

**Projection Proﬁle:** Each feature vector value is calculated

by summing over the pixel values in the corresponding image column. Figure 2 shows the plot of a typical feature

vector.

**Upper/Lower Word Proﬁle:** Upper/lower word proﬁle

features are computed by recording, for each image column,

the distance from the upper/lower boundary of the word image to the closest “ink” pixel. If an image column does not

contain ink, the feature value is computed by linear interpolation between the two closest deﬁned values.

**Background to Ink Transitions:** This feature (see Figure

5) records, for every image column, the number of transitions from the background to an “ink” pixel (determined by

thresholding).

# 3.2 Classifiers

The system has been tested with 3 classifiers: Self Organising Map, K-Means and Dynamic Time Warping. The classifiers are described in brief below. These classifiers are used while using Zernike feature or 400-dimensional feature. No classifiers were needed to be used while using DTW.

## 3.2.1 Self Organizing Map

A self-organizing map consists of components called nodes or neurons. Associated with each node is a weight vector of the same dimension as the input data vectors and a position in the map space. The usual arrangement of nodes is a regular spacing in a hexagonal or rectangular grid. The self-organizing map describes a mapping from a higher dimensional input space to a lower dimensional map space. The procedure for placing a vector from data space onto the map is to first find the node with the closest weight vector to the vector taken from data space. Once the closest node is located it is assigned the values from the vector taken from the data space. [12]



**Figure 6: SOM map (4 x 4) of music symbols.**

## 3.2.2 K-Means

Given a set of observations (x1, x2, …, xn), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets (k ≤ n) S = {S1, S2, …, Sk} so as to minimize the within-cluster sum of squares (WCSS):



where μi is the mean of points in Si.

# 4. ReTrieval of Query Sequence

For searching a query word Q from the collection of

document images, Q is first segmented into primitives as explained in Section 3.1. Next, we find out most similar codebook models of \_m for each primitive segments. Q is then encoded into a sequence of labels Lq1Lq2 : : :Lqt, where Lqi 2 Lm and t is the number of primitives in Q. To handle noise, ‘c’ nearest codebook models are also stored for each query primitives.

Now, the objective is to find words that have similar sequence of labels. Thus, the matching between query word Q and a target word W is formulated as matching of 2 sequences of primitives. As, primitives are labelled by codebook primitives Lm, the problem is to match primitive label strings of query and target word.

Approximate string matching algorithm [2] has been

used in our system for text searching. This method has

frequently been used in the literature to refer to a class of pattern matching techniques, by which k errors are allowed between a pattern string S and a text string T. The length of the strings S and T may be different. The algorithm finds all substrings of the text T that have at most k errors (character that are not same) with the pattern S. When k = 0 (no mismatches) it is simple string matching algorithm.

## 4.1 Self Organizing Map

In our system a SOM of is trained with features extracted from many symbols. The features of symbols in query and text are extracted.

A matrix C of order is created as follows:

where

ASM is used with help of the matrix to search the query string in the text string.

## 4.2 K-Means

When a query string is to be searched in a text string, the features of the components of the query and text of length and respectively are extracted.

The system is trained with features of many symbols and clustered into classes. The cluster centres are calculated by mean of the elements of the cluster. The distance of feature of a symbol from all the cluster-centres is calculated. A weighted mean of nearest 3 vectors is considered as nearest vector. A matrix of order is calculated as follows:

where

Then approximated string matching is used with help of matrix to find the best match of query string into the text string.

## 4.3 Dynamic Time Warping

Dynamic time warping (DTW) is an algorithm for measuring similarity between two sequences which may vary in time or speed. DTW is a method that allows a computer to find an optimal match between two given sequences (e.g. time series) with certain restrictions. The sequences are "warped" non-linearly in the time dimension to determine a measure of their similarity independent of certain non-linear variations in the time dimension.

Here DTW is used on two signals of 4 multidimensional features (): projection profile, upper and lower word profile and foreground transition. These features are extracted from the image after normalising them. The DTW distance between two signals I1 and I2 is calculated using a matrix D.

where

Finally, the matching cost is normalized by the length of the warping path . If the length of a features is , then the DTW distance between 2 symbols are .

For a text of length and a query of length a matrix of order is created as following:

Then approximated string match (ASM) is used with help of the matrix to find the best matches.

# 5. Result and discussions

## 5.1 Data collection

We have used the CVCMUSCIMA database [3] to evaluate our system. This dataset contains ground truth of handwritten music score images. It has 1,000 music sheets written by 50 different musicians. Though, the dataset has been especially designed for writer identification and staff removal tasks, the musical scores are used for score-word searching. 100 musical document and 15 query samples are considered.

## 5.2 Ground Truth Creation

As the input dataset taken does not contain ground truth for document retrieval, tool has been created to create ground truth. The ground truth for 50 documents and 10 queries are created with it. The tool stores the position of matches as following:

query\_file\_name x1 y1 x2 y2

Where (x1,y1) is co-ordinate of top-left corner of the bounding box of the query and (x2,y2) is the bottom-right corner co-ordinate.

## 5.3 Performance Metric

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Precision and recall has been used as performance metric and the output is plotted in a PR-Curve.

## 5.4 Qualitative Result

Some of retrieval results are shown in the following figures.



1. Query





1. Retrieval result for the shown query

**Figure 7: Example of retrieval results of a query in some texts.**

## 5.4 Quantitative Result

The following figures show the precision-recall graph for each feature and classifiers.

**Figure 8: Example of retrieval results of a query in some texts.**

The best result is from Zernike feature and SOM. The result for different number of clusters is shown below.

**Figure 9: Example of retrieval results Zernike feature and K-Means for different number of classes.**

# 6. Conclusion

In this system a new approach to musical document retrieval is shown. But there are scopes for improvements using this approach by extending the investigation to more accurate segmentation and classification and in future we plan to do it.

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