Writer Identification In Music Score Documents Without Staff-Line Removal

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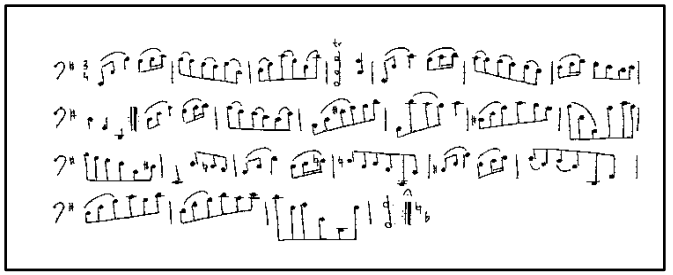
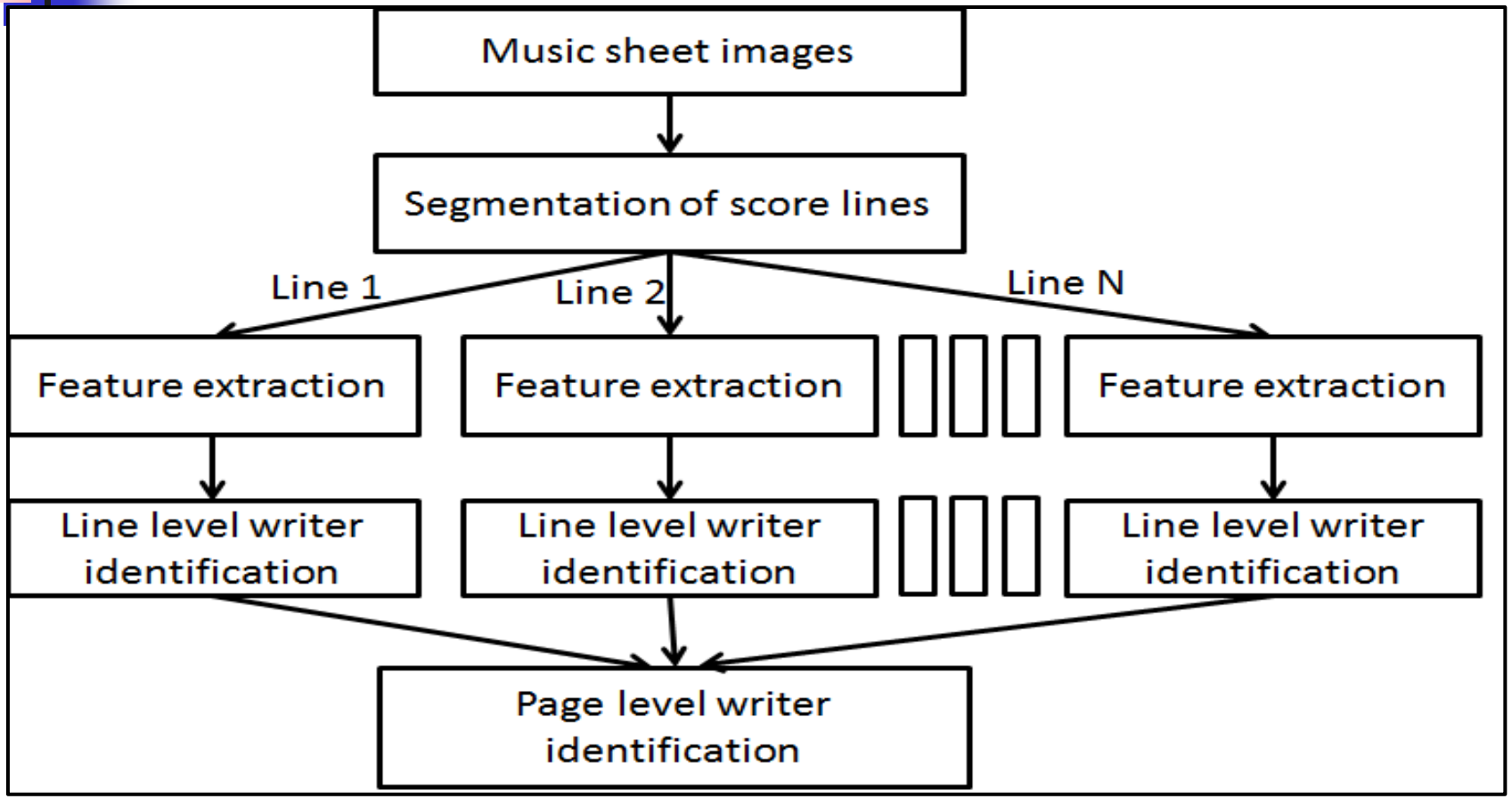
Introduction

- Writer identification is always a challenging task because of various writing styles
- In the existing pieces of writer identification work from musical sheets , staff lines are removed first to ease the writer identification task
- Here we propose a writer identification method without staff line removal
- To the best of our knowledge this is first work of writer identification without staff line removal.

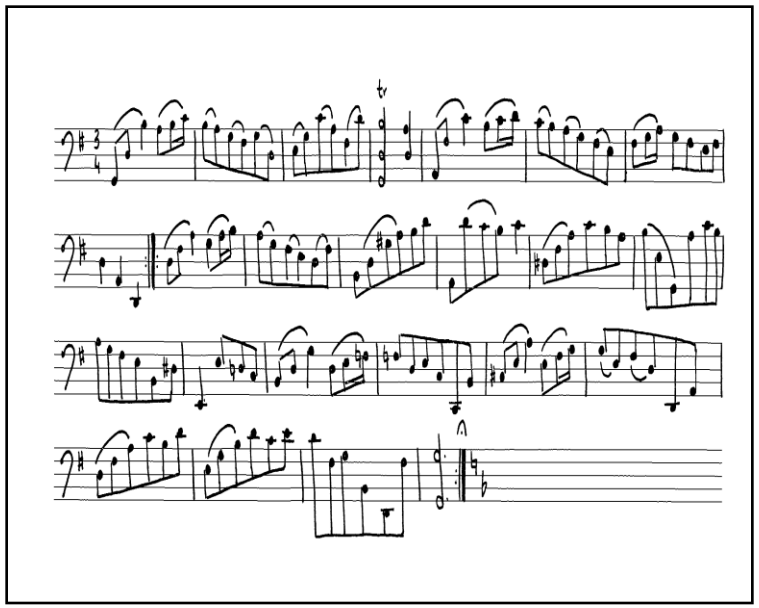


Block Diagram of the Proposed System



Dataset

Examples of a Music Page from the dataset



- CVC-MUSCIMA dataset [8]
- 1,000 music pages written by 50 different writers.
- Every writer has 20 different music pages.
- Dataset divided in two parts for training and testing.

[8] A. Fornes, A. Dutta, A. Gordo and J. Llados, The ICDAR 2011 music scores competition: staff removal and writer identification, in: *Proceedings of the International Conference on Document Analysis and Recognition*, 2011, pp. 1511–1515.

Working Principle

- A writer identification framework using HMM in music score without removing staff lines.
- The music page is first segmented into music score lines and local gradient histogram (LGH) based feature has been applied in each music-score line to capture the writing style feature.
- These features are used to construct HMM models for each writer.
- For identification of an unknown music-sheet, the input image is segmented into music-lines and these lines are then fed to each of the HMM models.

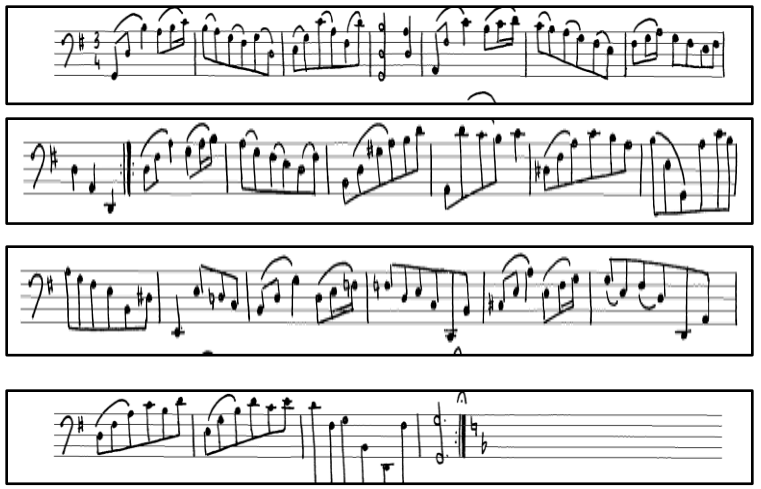
Working Principle (Contd..)

- HMM returns a log-likelihood score for each writer.
- Based on these scores the writer of the target music-score line image is decided.
- Finally, a page-level score is computed from these line-based scores using different parameters and the writer is identified for that page sample.

Score Line Segmentation

- Morphological dilation based method can be used for line segmentation.
- Length of the structuring element is considered as distance between two staff-lines.
- To get more robust results we are using the method due to Alireza et al. 2011 for line segmentation.

  (Alireza Alaei, Umapada Pal, P. Nagabhushan: A new scheme for unconstrained handwritten text-line segmentation. Pattern Recognition 44: 917-928 ,2011)



Feature extraction

- We have used Local Gradient Histogram (LGH) feature in our proposed system.
- In this feature extraction approach, a sliding window traverses the image from left to right in order to produce a sequence of overlapping sub-images.
- Each sliding window is sub-divided into 4×4 (4 rows and 4 columns) cells and from all pixels in each cell a histogram of gradient orientations is calculated.
- Considering 8 directions we obtained $8 \times 4 \times 4 = 128$ dim feature.

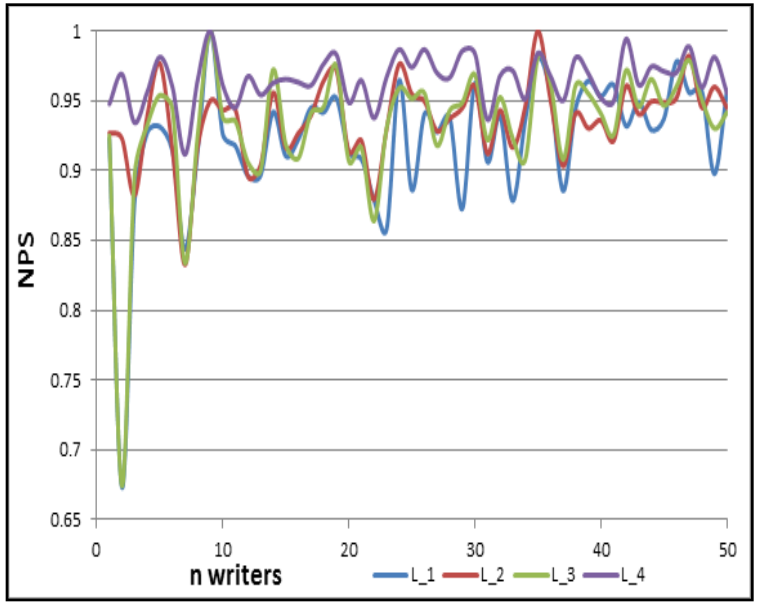
Line Wise Identification

- After extracting feature from training images of a particular writer, the obtained sequence of feature vectors were used to train HMM model for that particular writer.
- Thus, 50 HMMs were created for fifty different writers from the dataset. During testing, from each query test image, feature sequence is extracted and HMM generates the log-likelihood score of each writer.

Page Wise Identification (Contd..)

- Let the log-likelihood score for each line image be $S = \{S_1, S_2 \ldots\ldots S_N\}$ for N writer
- The probability $P = \{P_1, P_2 \ldots\ldots P_N\}$ of the writer's choice is calculated.
- Accordingly, to the probability scores the writers are ranked as $R = \{R_1, R_2 \ldots\ldots R_N\}$
- Here HMM estimates correct rank of writer 10 for line 1, 3 and 4 but in case of line 2, other writer (writer no. 35) have better rank.

Normalized probability Score



Page Wise Identification

- To avoid the confusion of line wise detection and identify the original writer of a music page, we assign a weight value $W=\{W_1, W_2 \ldots . W_N\}$ to the writers according to their rank (R_i). (N = no of writer and n = no. of lines in a musical page)

Weight assigning functions

Decay function	Description
Uniform function	$W = K$
Inverted distance	$W = \frac{N}{n}$
Inverted distance squared	$W = \frac{N}{(n^2)}$
Exponential decay	$W = \exp(-(a * n))$
Sinusoidal	$W = \mathrm{Sin}[\frac{N}{(n^5)}]$
Linear negative slope	$W = (-n + N)$

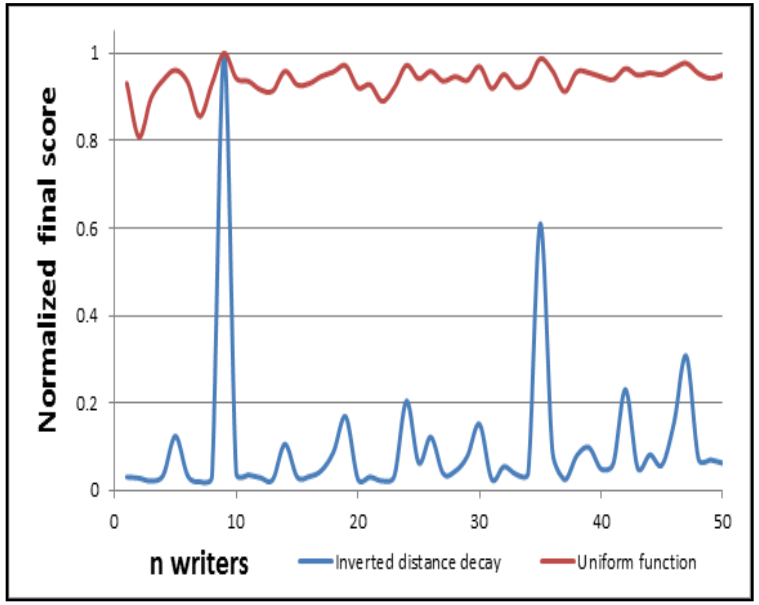
Page Wise Identification (Contd..)

- For m number of score lines corresponding to a music page, the final score F_i of i^{th} writer is estimated as

$$F_i = \sum_{j=1}^{m} [W_{ij} * P_{ij}]$$

- Where, P_{ij} and W_{ij} are probability score and weight assignment for j^{th} line, respectively

Normalized final score (of a page)



Inverted distance decay indicates clearly that writer no of this page is 10

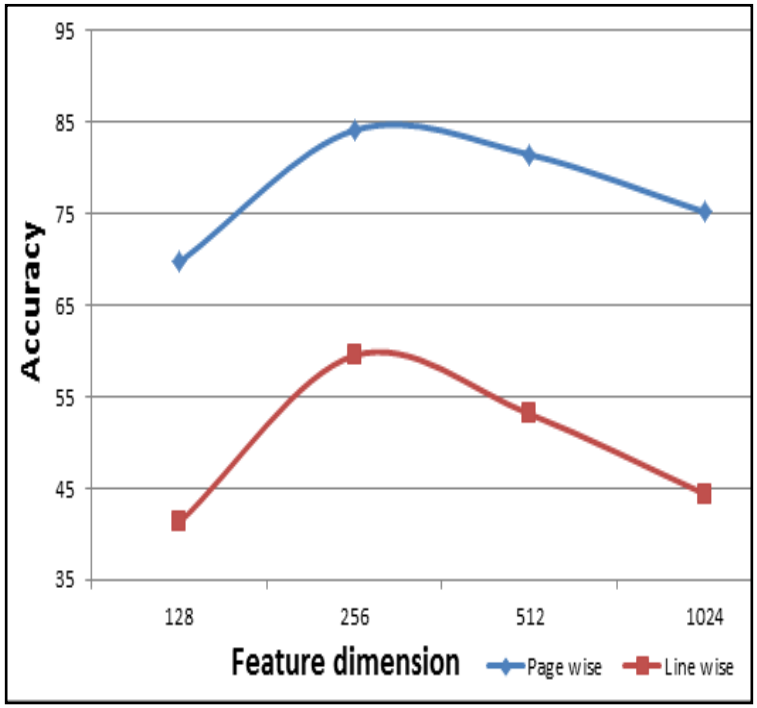
Line and Page Wise Identification Performance

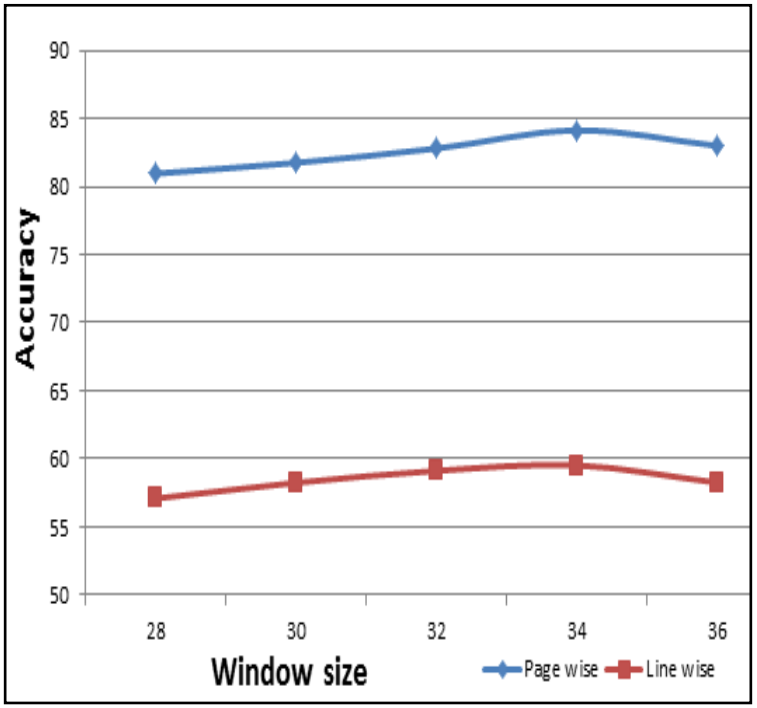
Page wise identification accuracy

Weight function	Accuracy
Uniform function	77.78
Inverted distance	84.13
Inverted distance squared	83.33
Exponential decay	82.54
Sinusoidal	82.54
Linear negative slope	80.16

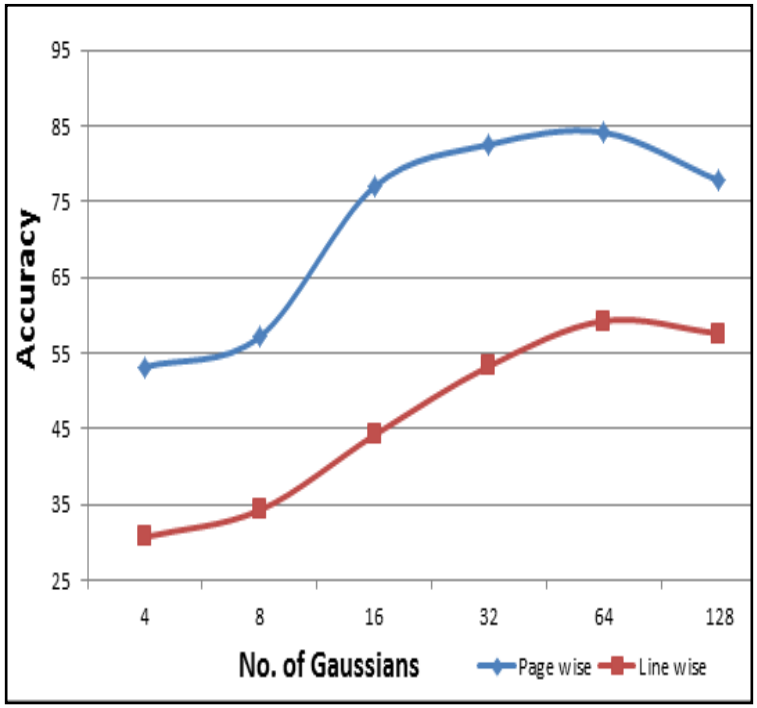
- 'Inverted distance' function gives the best identification rate.
- We noted that there is a significant improvement in page level writer identification compared to line level writer identification.

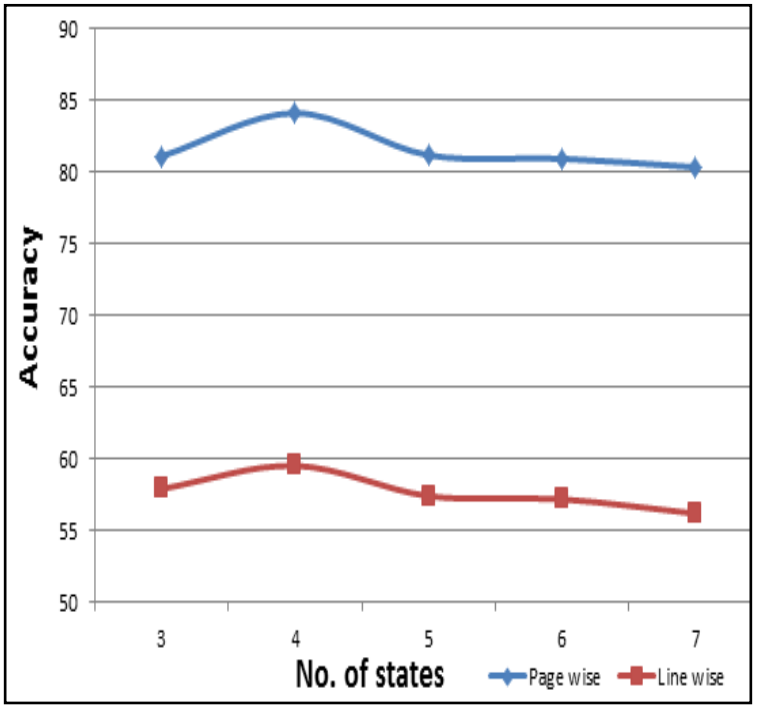
Results : Identification vs Variable Feature Dimension & Window Size



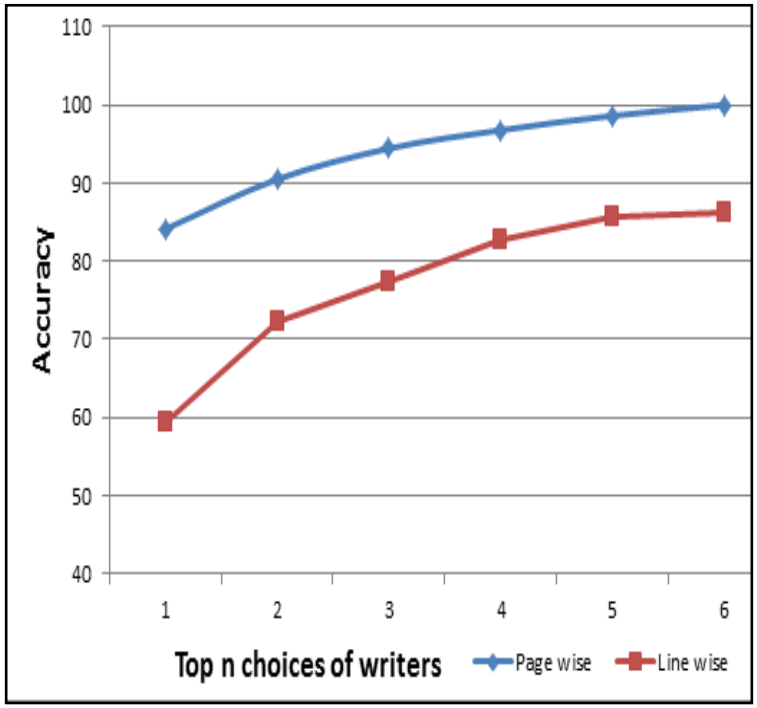


Results : Identification vs Variable Number of Gaussians & Number of States



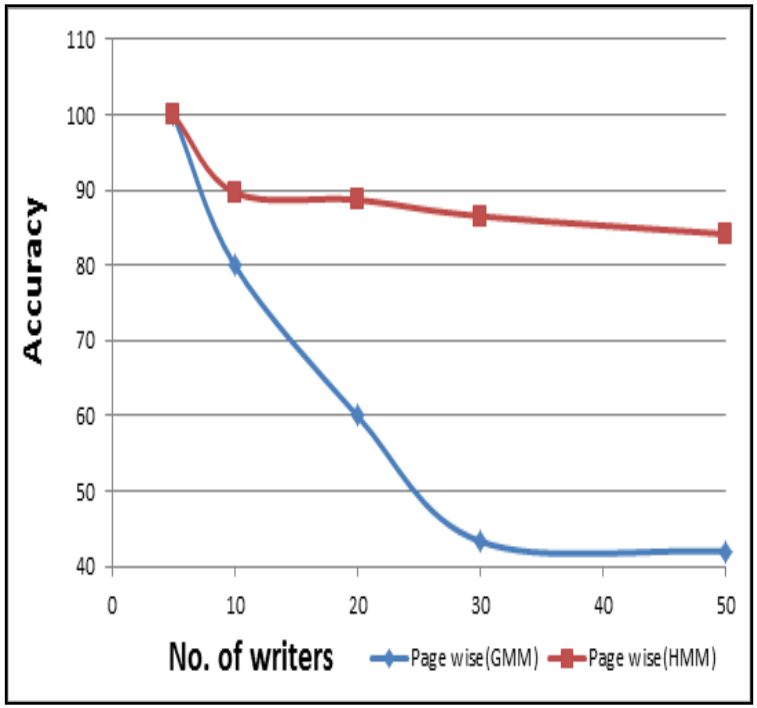


Results :Top n Choices of Writers



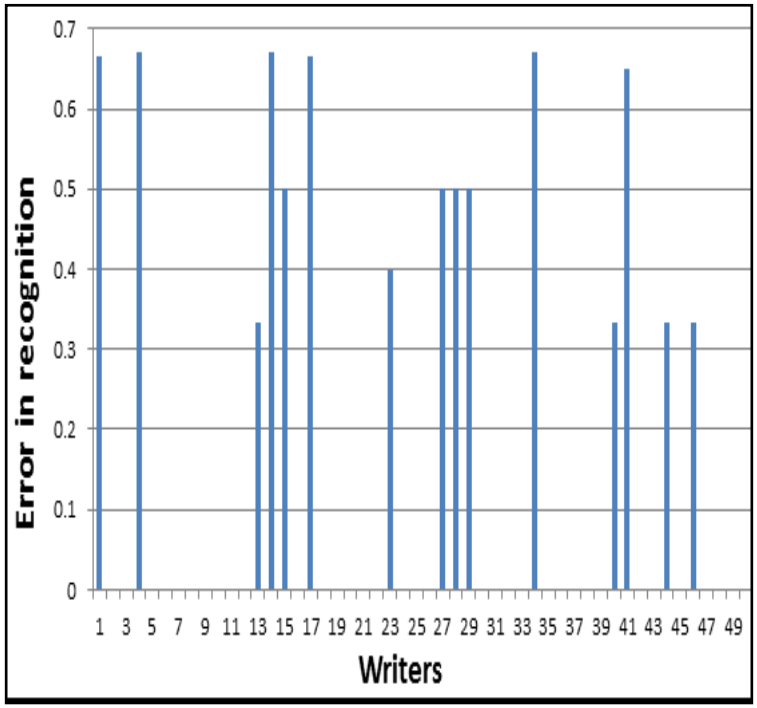
- Top n denotes that the true writer is present among the n-best hypotheses.
- It is to be noted that with 6 top choices, the page level identification result reached to 100%.
- With these 6 choices the line level performance was 85.76%.

Results: HMM vs GMM



- We have compared our HMM-based approach with Gaussian Mixture Model (GMM) based approach.
- GMM [12] is used here to create a model for each music writer. The distribution of the feature vectors extracted from a person's handwriting is modelled by a Gaussian mixture density.

Error Analysis



- Main reasons of errors
  - less number of music symbol present in a music page.
  - some of the music pages create confusion with other writers

Error Analysis (Contd..)

- Same writing style causes error in identification.
- High confusion between writer 17 and writer 42.

Conclusions

- Writer identification from musical sheets is a challenging task and all the existing pieces of work done after staff line removal.
- Here we propose a writer identification method without staff line removal and this is first work of writer identification without staff line removal
- We obtained 84.13% accuracy which is not very high and we need to improve the results.

Reference

- [1] I. Bruder, T. Ignatova, L. Milewski, Integrating knowledge components for writer identification in a digital archive of historical music scores, in: *Proceedings of the Joint ACM/IEEE Conference on Digital Libraries*, 2004, pp. 397.
- [2] A. P. Dempster, N. M. Laird, and D. B. Rubin. "Maximum likelihood from incomplete data via the EM algorithm*." In Journal of Royal Statistical Society, 39:1–38, 1977.*
- [3] H. Melin, J. Koolwaaij, J. Lindberg, and F. Bimbot. "A comparative evaluation of variance flooring techniques in HMM based speaker verification". *In Proc. of the 5th Int. Conf. on Spoken Language Processing, pages 2379–2382, 1998.*
- [4] A. Fornes, J. Llados, G. Sanchez, H. Bunke, Writer identification in old handwritten music scores, In *proc. of the International Workshop on Document Analysis Systems*, 2008, pp. 347 – 353.
- [5] A. Fornes, J. Llados, G. Sanchez, H. Bunke, On the use of textural features for writer identification in old handwritten music scores, In *Proc. of the International Conference on Document Analysis and Recognition*, 2009, pp. 996–1000.
- [6] A. Gordo, A. Fornes, E. Valveny, J. Llados, A bag of notes approach to writer identification in old handwritten musical scores, in: *Proceedings of the International Workshop on Document Analysis Systems*, 2010, pp. 247– 254.


Thank You!