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Chapter 5: Analysing the Visual Patterns of the Zhangzhung Nyengyü *Tsakali* Collection Using Machine-Learning Approaches

Abstract: This research forms part of a broader study that seeks to uncover the obscure history of the production and use of the Zhangzhung Nyengyü *tsakali*, or initiation cards, employed in various Tibetan rituals. This study employs multiple pattern-analysis techniques on the digital images of this collection to address specific research questions. In this work, the similarity between handwriting is analysed using the handwriting analysis tool (HAT); the sieve print of the writing support is analysed using the line detection tool (LDT); and the subjects depicted in *tsakali* are detected using the visual-pattern detector (VPD). These software tools were developed for manuscript analysis at the Centre for the Study of Manuscript Cultures. The initial findings highlight the potential for pattern analysis and its relevance to manuscript research, especially in the context of large collections. We briefly describe the methods used and discuss the preliminary results obtained from each.

1 Introduction

In recent years, automatic pattern analysis using machine-learning approaches has emerged as a potent and valuable tool for studying written artefacts when developed and applied properly. Such methods should be developed with close consideration of the actual research questions arising from manuscript studies, rather than relying solely on standard datasets and evaluation metrics devised by computer scientists in isolation. Furthermore, the application of these methods and the interpretation of their results should be undertaken in direct collaboration with domain experts in manuscript studies.

Several works have been published by computer scientists on the analysis of historical manuscripts using computational approaches, few of which can be easily and independently used by scholars. On the other hand, pattern analysis

https://doi.org/10.1515/9783111623214-007

software tools (PAST)[1] comprise a suite of scientific software tools designed for the analysis of both visual and tabular patterns in data derived from the study of ancient written artefacts. Each tool in this set is designed to have an easy-to-use graphical user interface (GUI). Furthermore, each tool is tested by relevant experts from manuscript studies. Therefore, we employed three tools from PAST in this case study to analyse the handwriting styles, writing supports and drawing instances within the collection of sixty-five Zhangzhung Nyengyü *tsakali*. The initial results of our study underscore the potential for pattern analysis and its extensive applicability in the field of manuscript research.[2] In this chapter, we will focus on the discussion and interpretation of the results and their influence on the next phases of this research. As stated in Chapter 1, this set of *tsakali*, despite similarities in style, may contain cards that may have been added to the collection later. We also know that *tsakali* were usually used in sets, depending on their purpose or user. There is a large number of cards of a similar style, preserved in the Triten Norbutse Monastery in Kathmandu, that may be a good reference for future research. We cannot exclude the possibility that some of the cards preserved in Triten Norbutse are part of our studied collection as well. Thus, there is a need for automatic pattern analysis in order to allow for the efficient search and quantitative comparisons of different sets based on particular features.

The *tsakali* are not bound and can easily be mixed with other sets of the same size. Moreover, the objects and figures depicted on the cards are chosen for specific types of performances, making each collection unique. Thus, we do not know whether these sixty-five cards comprise a full set or were just accidentally separated from a much larger collection or collections. As computational methods are good for working with large amounts of data, they are helpful in this study.

The starting point for our research is to produce images of a sufficient quality that can be used for further processing and analysis. The photographs produced with MSI, as described in Chapter 4, were very appropriate for our purposes. The digitisation process resulted in high-resolution TIF images. Each image contains three cards, and every card has a resolution of about 2280 × 4870 pixels. The average height of the letters in these images is around 60 pixels, which is sufficient for a proper analysis of the handwriting.

1 Mohammed et al. 2022. The PAST software can be downloaded from <https://www.csmc.uni-hamburg.de/publications/software.html> (accessed on 29 July 2025).

2 The technical details and mathematical descriptions of these experiments have been published in Mohammed and Helman-Ważny 2022.

2 Handwriting style analysis

The *tsakali* have a very specific ritual function. Each card displays both an image, described underneath in red ink on the recto side, and a longer text written in black ink on the verso. The text on the verso is inseparable from the image and varies in length from card to card, written in the headless *ume* (*dbu med*) script in black and red ink.[3] This script is not standardised and displays the idiosyncrasies of individual scribes. Therefore, analysing the handwriting styles with the handwriting analysis tool (HAT)[4] can be useful in determining whether all the cards were written by the same person. Identifying different scribes can thus shed light on the production process and the artisans involved. The results of this analysis will be corroborated by other methods, such as paper and pigment analysis.

The HAT is utilised for this analysis to measure the similarity between handwriting styles on different pages. This software tool leverages the training-free Normalised Local Naïve Bayes Nearest Neighbour (NLNBNN), facilitating the analysis of handwriting styles without requiring any labelled data, which was unavailable in this case. Several hundreds of visual features have been automatically detected and mathematically described using this tool on the contours of the ink trace. After that, a similarity score is calculated by the software for each handwriting style (scribe), providing the user with a relative comparison between the styles against a given unknown handwriting.

In this test, the similarity between handwriting on both the recto and verso sides of all sixty-five cards was measured. The results indicate that the handwriting on all sides of all images is very similar overall. Nevertheless, the similarity value of the handwriting on the verso sides of Tsakali G and Tsakali H is always half (or less) compared to all other instances; refer to Figs 1a–b. Consequently, a second test was conducted to assess the similarity of the handwriting on the verso sides of Tsakali G and Tsakali H with that on the verso sides of all the other cards' images. This test revealed no significant similarity with any image in the collection, indicating the possibility that the handwriting on these two surfaces might belong to a different scribe. Further investigation was undertaken by other, independent methods to confirm this hypothesis.[5]

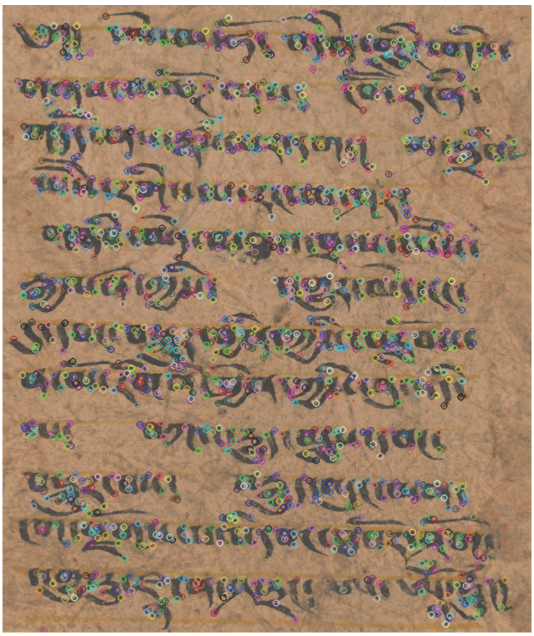
The amount of handwriting on each card is only a few lines of text. This is typically not enough for training-based approaches, but sufficient for training-free

3 See Chapter 1 for translation.

4 Mohammed 2020a, software.

5 See Chapters 3 and 10.

machine-learning methods. Nevertheless, the results of any handwriting style analysis need to be interpreted very carefully, and the wider context of the analysis must always be considered.



a

Results for Tsakalis_19_20_21_v_PSC_P1

Rank	Directory	Score
•		•
•		•
•		•
19	Tsakalis_37_38_39_v_PSC_P2	3.6
20	Tsakalis_25_26_27_v_PSC_P2	3.6
21	Tsakalis_3_4_5_v_PSC_P2	3.1
22	Tsakalis_g_h_v_PSC_P2	0.8

b

Figs 1a–b: Results of handwriting style analysis using HAT. (a) Example of an analysed page. The coloured circles represent the location of the detected features on the ink trace of the handwriting. (b) One of the similarity scores generated by HAT, which shows the small similarity value with the text executed on the verso sides of Tsakali G and H compared to all the other cards in the collection.

The results generated by HAT are relative to the samples used in the analysis, and the summation of all similarity scores is always 100 per cent. This means that using different samples from the same scribes can lead to slightly different results, and adding or removing styles will affect the absolute values of the similarity measures, but not the relative similarity between any pair of samples.

If a sufficient number of samples is made available from other card collections in the region, one can group these samples by scribe based on the similarity values between their handwriting styles. Nevertheless, one must consider the fact that the handwriting styles of different scribes can share visual features due to several factors, such as sharing the same scriptural culture or mimicking a certain scribe or school of writing.

In this experiment, we iterated over all the folios, comparing each current folio against all others. The results consistently indicated that the similarity value for this folio was always half or less than the value for any other folio in the dataset. The results indicate that the handwriting on all sides of all images is very similar overall. Nevertheless, the similarity value of the handwriting on two particular surfaces, identified as the verso sides of Tsakali G and Tsakali H, is always half (or less) compared to all other instances (refer to Figs 1a–b).

The strings in the 'Directory' column represent the exact folios in this dataset. As can be seen, this comparison has been done between twenty-two folios. Consequently, a second test was conducted to assess the similarity of the handwriting on the verso sides of Tsakali G and Tsakali H with the verso sides of all the other cards' images. This test revealed no significant similarity with any image in the collection, indicating the possibility that the handwriting on this page might belong to a different scribe.

3 Writing-support analysis

The cards were created by one or sometimes more laminated sheets of paper typically produced in the Himalayas.[6] However, two types of papermaking sieve print were detected during preliminary macroscopic observation of the analysed set,[7] and confirmed by multispectral imaging (MSI) and statistical image processing,[8] which suggests that more than one type of papermaking mould was

6 See Chapter 6.

7 See Chapter 1.

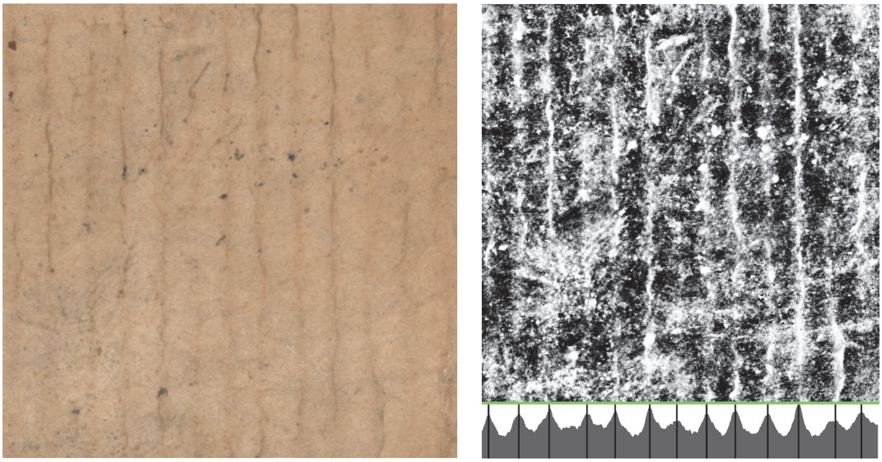
8 See Chapter 4.

used in the papermaking process. Besides raw materials, paper can be distinguished by technological features that originate directly from the papermaking process. The actual method of making paper in Tibet seems to have evolved very little over the centuries, with each sheet of paper made and then dried on an individual papermaking mould. This mould type is called 'floating' because it is placed on a water surface such as that of a lake, pond, river or, later, a wooden basin. It is usually made of a wooden frame with a thin cotton cloth spread on it. Thus, the detected marks of laid lines were unusual and suggested the use of an additional type of mould that was not typically used in Tibet. It is however important to note that the other type of technology is identified increasingly often during the examination of paper macroscopic features in Tibetan books. Significant numbers of 'laid papers' were found in Tibetan books in the Dunhuang collection, as was also the case for more recently studied types of paper used in Mustang and Dolpo manuscripts. This is why we used the line detection tool (LDT)[9] to find out how many types of paper were used in this collection. The presence of laid paper in the collection could support the hypothesis that the paper used for making this set of *tsakali* could have been acquired from more than one source.

The LDT is used to analyse the writing supports in these images. This tool is based on the method described as follows: the contrast of the selected images is first enhanced using contrast limited adaptive histogram equalisation (CLAHE).[10] The goal of utilising this approach is to reduce the interference of background texture and enhance the visibility of the lines in the writing support. After that, the lines are detected and localised by calculating the vertical projection of pixel values in the image. Although this approach assumes the lines to be mostly straight and parallel to each other, its utilisation is justified due to the uniform nature of these lines. The limited irregularities and distortion found in the calculated projections are rectified by a smoothing technique, namely a Gaussian filter. Finally, a histogram is constructed from the smoothed projections in order to locate the peak for each line, which refers to its estimated location in the writing support (Figs 2a–b).

9 Mohammed 2020b, software.

10 Pizer et al. 1987.



a b

Figs 2a–b: Results of the writing-support analysis. (a) One sample from the analysed images. (b) The histogram automatically generated by LDT.

A square region of 30 × 30 mm has been analysed from three different samples using the LDT. Several measurements have been calculated automatically for all samples, such as the estimated density and spacing of detected lines. The lines observed in Tsakali D have slightly less density, which might indicate the use of a different papermaking source (see Chapter 6). The integration of results from different types of analysis and the comparison with results from other collections can lead to better interpretations of these findings.

Since these measurements are absolute and unique to each type of writing support, they can be directly compared with samples from other collections to support the study of paper production in the region. While the colour images of this particular collection were sufficient to detect the sieve line, the visibility of these lines was clearly better in some bands of the MSI images. This observation might prove handy in cases where colour images are not sufficient for the analysis of some collections.

4 Drawing-elements analysis

The *tsakali* are used in numerous ritual situations, such as empowerment rites, ritual mandalas, the transmission of teachings, substitutes for ceremonial items, visualisation aids and funerals. The subjects depicted in the *tsakali* cover a vast range, from main deities and protectors to their various power attributes and appropriate offerings (see Chapter 3). Detecting these visual elements in different instances, and maybe in other collections, can greatly facilitate the retrieval process of relevant semantic content.

The visual-pattern detector (VPD) is used in order to detect and allocate the relevant visual elements without the need for any ground-truth annotations. This tool is based on a method that detects distinctive features in every visual element and learns the spatial relations between these features and the estimated centre of this element.[11] After that, a saliency map is constructed based on the features detected and their similarity to the original query image. This saliency map is used to allocate and identify the visual elements in each image.

Only one example is used per pattern in this analysis, as the method used is a training-free approach. The VPD detects similar visual patterns in this collection automatically without the need for any annotations, and the recall-precision balance of detected patterns, which is the main parameter for most pattern detection approaches in machine learning, can be intuitively controlled using visualised examples. The pattern in Figs 3a–c is a bowl made of a human skull. Such human-skull bowls were often used in Tibetan rituals.

Given the small number of images in this collection, one can, with a reasonable amount of effort and time, search manually for visual patterns and objects without any support from computational methods. But this collection is only one of many other collections from the same region, and possibly other neighbouring regions. Searching for similar visual patterns across collections can help in revealing new insights about the practices, interaction and transmission of these cultures. Furthermore, the exact measure of similarity between detected patterns can be used in order to evaluate and quantify gradual changes across space and time.

11 Mohammed 2021, software.

a b c

Figs 3a–c: Example results from VPD presenting three automatically detected instances of human-skull bowls.

5 Discussion and conclusions

In this study, we applied machine-learning approaches to analyse different aspects of the Zhangzhung Nyengyü *tsakali* collection using the visual patterns in its digitised images. The findings from this research demonstrate the relevance of automated pattern analysis in this field of manuscript studies, and the potential for extending its applicability to other collections.

The handwriting style analysis using the handwriting analysis tool (HAT) revealed significant similarities among most cards, with notable exceptions suggesting contributions from different scribes. This insight can deepen our understanding of the production processes and scribes involved. The writing-support analysis with the line detection tool (LDT) identified variations in the papermaking techniques used, indicating multiple sources for the used paper in these cards. These results contribute to our knowledge of historical papermaking practices and trade in the region. Finally, the visual-pattern detector (VPD) successfully identified recurring visual elements, such as human-skull bowls, across the collection. This capability allows for efficient retrieval and comparison of visual motifs within and across collections, offering new perspectives on cultural and ritual practices.

Overall, this research highlights the effectiveness of integrating machine-learning tools into manuscript analysis. These tools not only enhance our ability to detect and interpret patterns, but also open new avenues for cross-collection comparisons and historical insights. Future research can build on these findings by incorporating larger datasets and further refining the analytical techniques, thereby advancing our understanding of the historical and cultural contexts of these artefacts.