Ancient Maya Writings as High-Dimensional Data: a Visualization Approach

Gülcan Can[1], Jean-Marc Odobez[1], Carlos Pallán Gayol[2], and Daniel Gatica-Perez[1]

[1]Idiap Research Institute and École Polytechnique Fédérale de Lausanne (EPFL), Switzerland
[2]Institute for Archaeology and Cultural Anthropology, University of Bonn, Germany

1 Introduction

The ancient Maya civilization flourished from around 2000 BC to 1600 AD and left a great amount of cultural heritage materials, in the shape of stone monument inscriptions, folded codex pages, or personal ceramic items. All these materials contain hieroglyphs (in short glyphs) written on them. The Maya writing system is visually complex (Fig. 1) and new glyphs are still being discovered. This brings the necessity of better digital preservation systems. Interpretation of a small amount of glyphs is still open to discussion due to both visual differences and semantic analysis. Some glyphs are damaged, or have many variations due to artistic reasons and the evolving nature of language.

Signs following ancient Mesoamerican representational conventions end up being classified according to their appearance, which leads to potential confusions as the iconic origin of many signs and their transformations through time are not well understood. For instance, a sign thought to fall within the category of "body-part" can later be proven to actually correspond to a vegetable element (a different semantic domain). Similarly, several signs classified as "abstract", "square" or "round" could actually be pars-pro-toto representations of a larger whole.

Fig. 2 illustrates the challenges to analyze Maya glyphs visually. We pose it that adding functionalities that take context (i.e., co-occurrence statistics of other glyphs, characteristics of the data) and part-whole relations (i.e., highlighting diagnostic parts) into account would bring guidance during decipherment tasks. The tools we envision are different from existing almanac-by-almanac visualization systems [15]. They are also more engaging for users (i.e. visitors in museums), and offer promising perspectives for scholars.

This motivates the study of data visualization. In this paper, we built a prototype for visualization of glyphs based on visual features. We introduce (1) an approach to analyze Maya glyphs combining a state-of-the-art visual shape descriptor, and (2) a non-linear method to visualize high-dimensional data. For the first component, we use the histogram of orientation shape con-

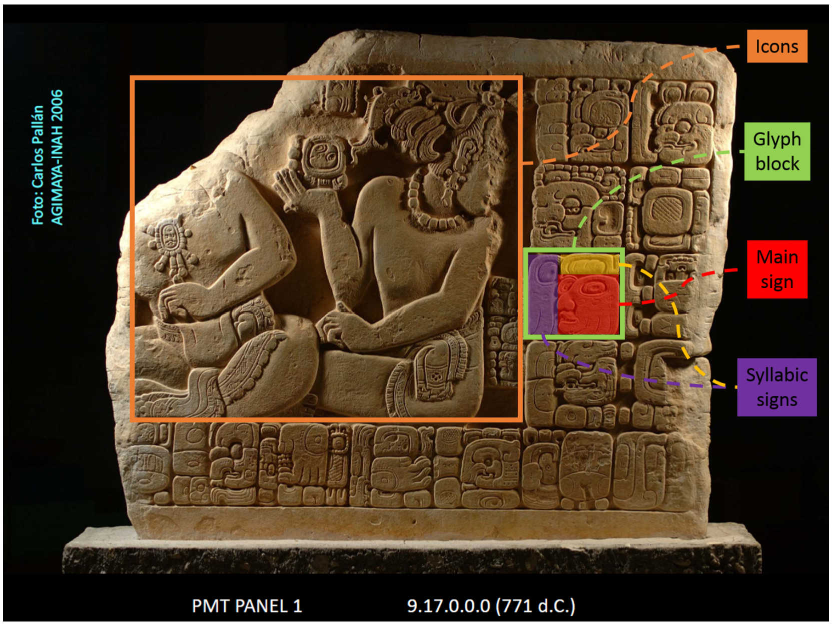

Figure 1: A stone inscription found in Pomona, Tabasco (Mexico), Panel 1 from 771 AD. Photograph by Carlos Pallan Gayol for the AJIMAYA/INAH Project © 2006. Instituto Nacional de Antropología de Historia, Mexico.

text (HOOSC) [13, 12, 11] which has similarities to other descriptors of the recognition literature [1, 3, 9], but is adapted to shape analysis [4].

For the second component, we use the t-distributed Stochastic Neighborhood Embedding (t-SNE) [16], which is a dimensionality reduction method from the machine learning literature that has value for Digital Humanities (DH), as it can highlight the structure of high-dimensional data, i.e., multiple viewpoints among samples. As analysis of DH data is often based on attributes like authorship, produced time, and place, observing these variations as smooth transitions with

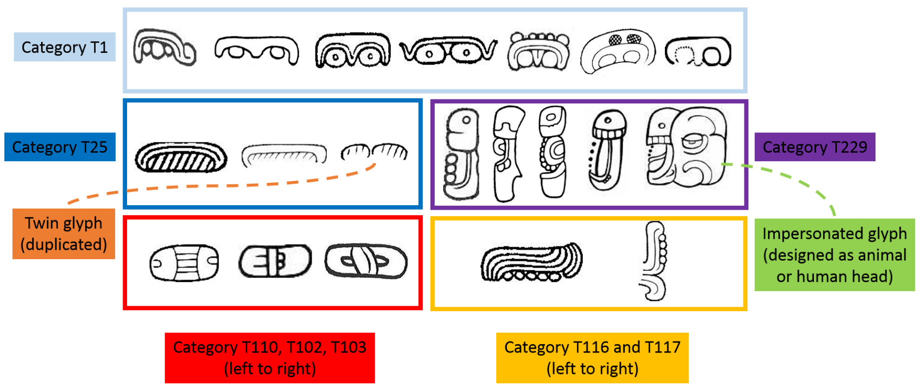

Figure 2: Maya glyph samples from several categories (according to Thompson's catalog) that illustrate the within-class variety and between-class similarity.

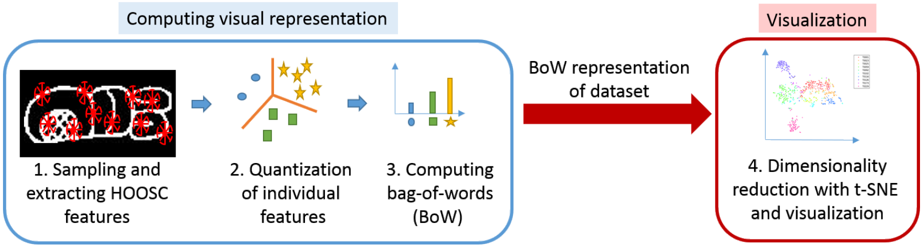

Figure 3: Overall flow for visualization with t-SNE.

t-SNE becomes a relevant feature.

We show that the proposed visualization methodology is useful to analyze the extent of spatial support used in the shape descriptor and to reveal new connections in the corpus through inspection of glyphs from stone monuments and glyph variants from catalog sources. In particular, we hope that the presentation of our use of t-SNE can motivate further work in DH for other related problems.

2 Methodology

The analysis process is illustrated in Fig. 3. First, for each glyph, a standard visual bag-of-words representation (BoW) is computed from the HOOSC descriptors. Second, dimensionality reduction is performed on the BoW representation of a glyph collection to generate the visualization. The main steps are described in sections 2.3 and 2.3.

2.1 Datasets

We illustrate our visualization pipeline on two individual Maya glyph datasets.

Monument Data: We use a subset (630 samples from 10 classes, Fig. 4) of hand-drawings [12], corresponding to syllabic glyphs inscribed in monuments. These samples are collected by archeologists (as part of Mexico's AJIMAYA project) from stone inscriptions spread over four regions (Peten, Usumacinta,

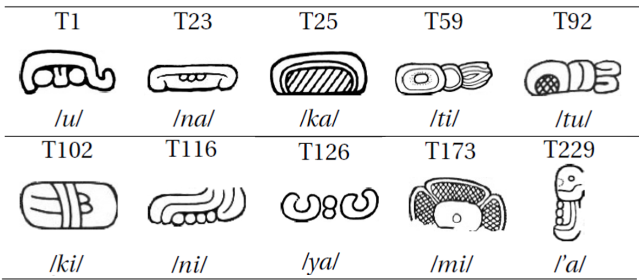

Figure 4: Sample glyph images, corresponding Thompson annotations, and syllabic values (sounds) of selected 10 classes from the syllabic monument glyph dataset.

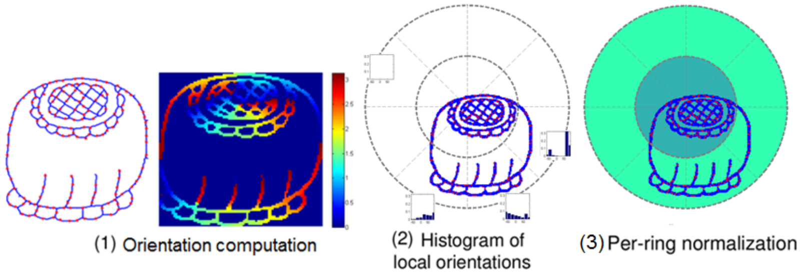

Figure 5: HOOSC computation at a sample position p of the shape, which includes: computation of 1) pixelwise orientations, 2) histogram of local orientations in each spatial bin, and 3) per-ring normalization of the histograms.

Motagua, and Yucatan). As an additional source, around 300 glyph samples are taken from existing catalogs [14, 10].

Thompson Catalogue: We use 1487 glyph variants cropped from the Thompson's catalogue. These variants belong to 814 categories and are divided as main sign and prefix/suffix groups in the catalogue.

2.2 Visual Feature Representation

The HOOSC is a shape descriptor proposed in our research group for Maya glyphs [13]. It is computed in two main steps (Fig. 5). First, the orientations of a set of sampled points are computed. Secondly, for a given sampled position, the histogram of local orientations are computed using a small number N_a of angle bins forming a circular grid partition centered at each point. The HOOSC descriptor is obtained by concatenating all histograms, and applying per-ring normalization. Basic parameters are the spatial context sc, defining the extent of the spatial partition; the number of rings N_r; and the number N_s of slices in a ring. With $N_a = 8$, $N_r = 2$, $N_s = 8$, HOOSC has 128 dimensions. We have used HOOSC for usual retrieval and categorization tasks [7].

2.3 Dimensionality Reduction: t-SNE

Proposed in [6], SNE is a non-linear dimensionality reduction method. It relates the Euclidean distances of samples in high-dimensional space to the conditional probability for each point selecting one of the neighbors. These distributions are modeled as heavy-tailed t-distributions in [16] (t-SNE). t-SNE aims to find for each data point, a lower-dimensional projection such that the conditional probabilities in the projected space are as close as possible to those of the original space (measured with Kullback-Leibler divergence [8]).

In our application, first, we project the BoW representation to a 30-dimensional space using PCA, then applied t-SNE to these projections to get 2-dimension mapping. t-SNE keeps track of the local structure of the data as it optimizes the clusters globally.

3 Results and Discussion

The full-scale visualization of the glyphs are available at
https://www.idiap.ch/project/maaya/demos/t-sne/.

3.1 Glyph Monument Corpus Structure

Fig. 6 shows the monument corpus. The region encoded in the visual descriptor varies from almost the whole glyph ($sc = 1/1$) to small local parts ($sc = 1/8$). One question is how spatial context influences the visualization of the representation. Regarding the visual clusters, with the most global representation ($sc = 1/1$), our method extracts more distinct clusters, e.g. T229 and T126 in Fig. 7 (navy and magenta in Fig. 6 and 9). Please refer to Fig. 9 for roughly-colored clustered on the actual glyph images. As the descriptor gets more local, the categories with common patterns mix up (Fig. 6). Yet, our method is able to capture meaningful common local parts and maps the samples based on these

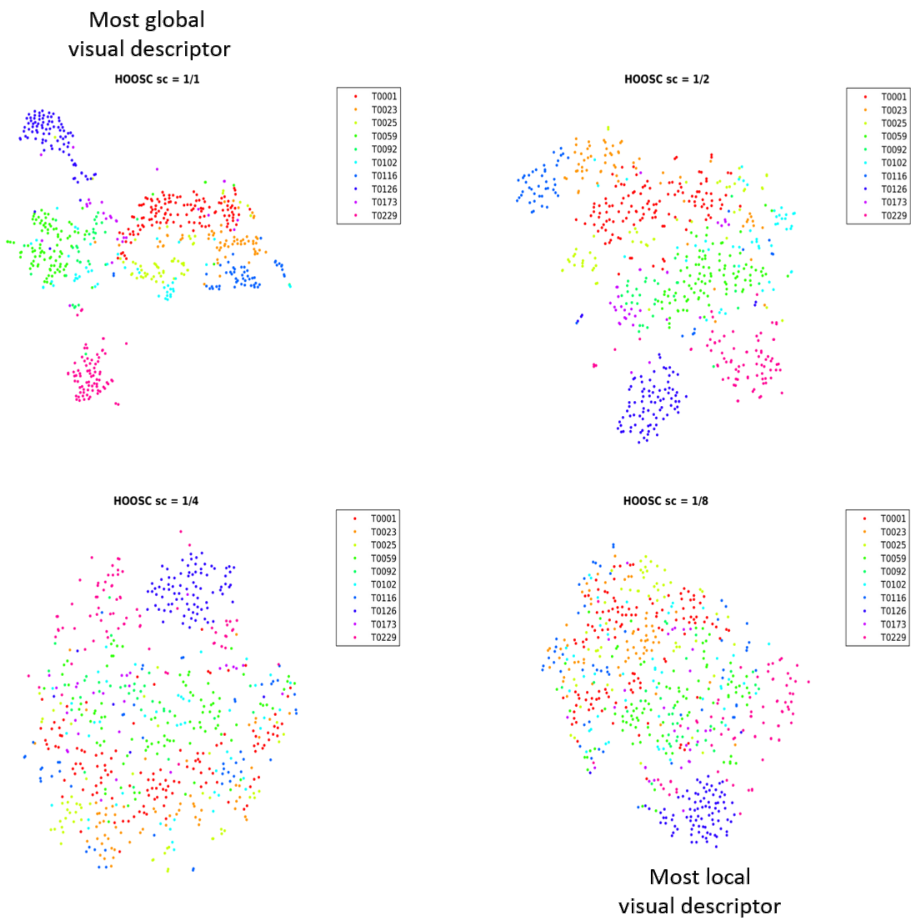

Figure 6: Monument data: t-SNE plots with visual representations obtained at 4 different spatial context levels.

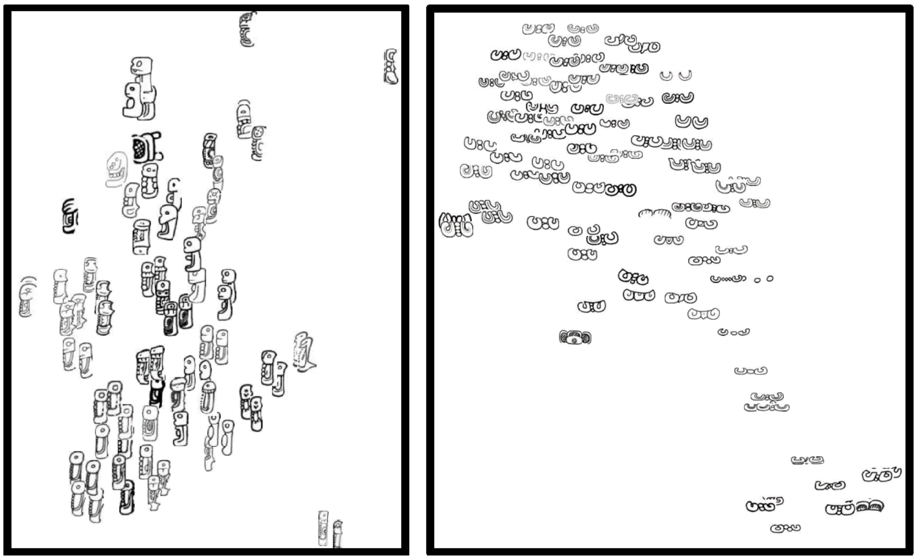

Figure 7: Monument data: Close-up of two clusters (T229 on the left and T126 on the right), corresponding to navy and magenta clusters in Fig. 6 with the most global HOOSC descriptor ($sc = 1/1$).

elements, i.e. parallel lines, hatches, and circles.

For Maya epigraphers in our team, a more neatly differentiated grouping of signs, such as that resulting from HOOSC with $sc = 1/1$ is preferable. However, work on the effects of parameter choice is required to obtain groupings that make more epigraphic sense. Clearer "borderlines", less "outliers", and less "intrusive" signs (e.g. T25 and T1) within each cluster would be desirable. Our results in this regard are preliminary, but they open promising research

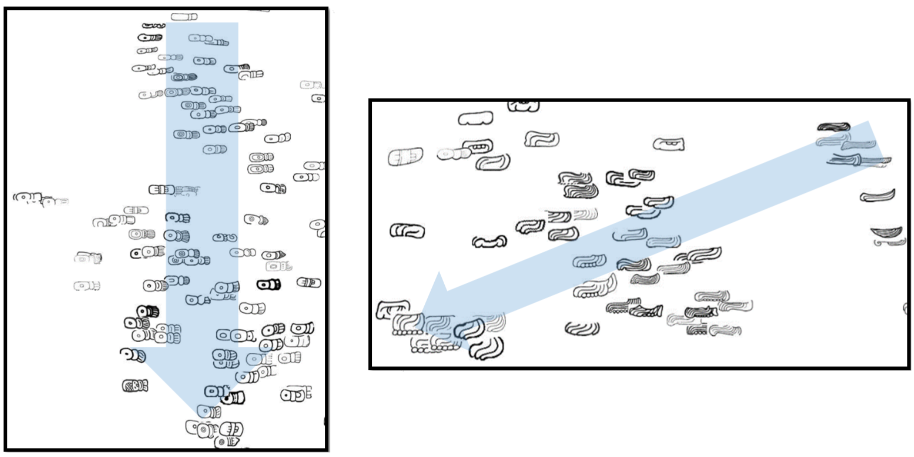

Figure 8: Monument data: Close-up of two clusters (T59 on the left and T116 on the right), which exhibit smooth transition between samples corresponding to place or temporal variations.

Figure 9: Monument data: Visualization of all class samples with the most global HOOSC descriptor ($sc = 1/1$).

questions.

Another important epigraphic point is that we observe interesting visual transitions between samples of the categories. Fig. 8 shows examples from category T59 (left) and T116 (right), which illustrate a smooth dilation of samples in one direction. These kind of observations are interesting for the archeologists, since they might correspond to modification of the glyph signs over time or place.

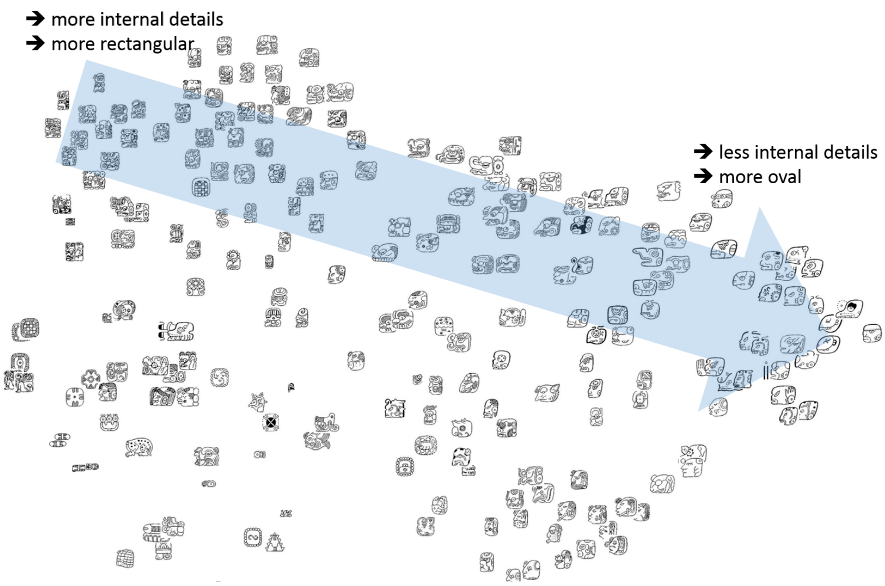

Figure 10: Catalogue data: A visual cluster of main signs from the Thompson catalogue, with the most global HOOSC descriptor ($sc = 1/1$). Many of them are impersonatedd main signs that corresponds to gods or animals. In this part of the visualization, the upper left part has more visually complex variants than the rightmost samples.

3.2 Glyph Variants from the Thompson Catalogue

From the visualization of glyph variants in Thompson's catalogue with the largest spatial context level ($sc = 1/1$), we observe that visually similar categories are grouped together, while exhibiting smooth transitions. These transitions may correspond to some characteristics of the data. Fig. 10 shows a cluster of personified main signs in which the degree of visual internal detail decreases in the indicated direction. We also observe separate visual clusters for hatched, horizontal and vertical glyphs.

4 Conclusion

Our goal in this study is to help DH scholars to visualize data collections not as isolated elements, but in context (visually and semantically).

Even though early catalogs are built based on visual similarities, i.e., Thompson [14] or Zimmermann [17] relied on graphic cards to study similar patterns and spatial distributions, the categorization methods were poorly understood and were not easy to reconfigure. Furthermore, due to the limited knowledge at the time about semantics and sign variants, these catalogs turned out to be inaccurate or outdated. Similarly, Gardiner's list [5] is insufficient to elucidate sign variability in the "Book of The Dead" [2].

With the proposed tool, however, considering details at different scales as semantic/diagnostic regions in the visualization can help archaeologists to discover semantic relations. In this way, overlapping notions such as "colors", "cardinal directions" and specific toponyms from earthly, heavenly or underworld realms can be studied in greater detail.

Finally, illustrating all variations with different visual focus in a fast and quantitative manner brings out the characteristics of signs. This also helps experts match samples from various sources (i.e. monuments, codices, and ceramic surfaces) to corpus data more efficiently; and trigger the decipherment of less frequent and damaged signs. Hence, our work is a step towards producing a more accurate and state-of-the-art sign catalog.

5 Acknowledgements

This work was funded by Swiss National Science Foundation (SNSF) as part of the MAAYA project.

References

[1] S. Belongie, J. Malik, and J. Puzicha. Shape matching and object recognition using shape contexts. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 24(4):509–522, April 2002.

[2] E.A.W. Budge. *The Book of the Dead: An English Translation of the Chapters, Hymns, Etc., of the Theban Recension, with Introduction, Notes, Etc.,*. Books on Egypt and Chaldaea. Open Court Pub., 1901.

[3] N. Dalal and B. Triggs. Histograms of Oriented Gradients for Human Detection. volume 1, pages 886–893. IEEE, 2005.

[4] Morris Franken and Jan C. van Gemert. Automatic Egyptian hieroglyph recognition by retrieving images as texts. pages 765–768. ACM Press, 2013.

[5] Alan H. Gardiner. *Egyptian grammar: being an introduction to the study of hieroglyphs*. Griffith Institute, Ashmolean Museum, Oxford, 3d ed., rev edition, 1957.

[6] Geoffrey E. Hinton and Sam T. Roweis. Stochastic neighbor embedding. pages 833–840, 2002.

[7] Rui Hu, Gulcan Can, Carlos Pallan Gayol, Guido Krempel, Jakub Spotak, Gabrielle Vail, Stephane Marchand-Maillet, Jean-Marc Odobez, and Daniel Gatica-Perez. Multimedia Analysis and Access of Ancient Maya Epigraphy: Tools to support scholars on Maya hieroglyphics. *Signal Processing Magazine, IEEE*, 32(4):75–84, 2015.

[8] Solomon Kullback and Richard A. Leibler. On information and sufficiency. *The annals of mathematical statistics*, 22(1):79–86, 1951.

[9] David G. Lowe. Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2):91–110, 2004.

[10] Martha J. Macri and Matthew George Looper. *The New Catalog of Maya Hieroglyphs: The Classic Period Inscriptions*, volume 1. University of Oklahoma Press, 2003.

[11] Edgar Roman-Rangel, Jean-Marc Odobez, and Daniel Gatica-Perez. Evaluating shape descriptors for detection of maya hieroglyphs. In *Pattern Recognition*, pages 145–154. Springer, 2013.

[12] Edgar Roman-Rangel, Carlos Pallan, Jean-Marc Odobez, and Daniel Gatica-Perez. Analyzing ancient maya glyph collections with contextual shape descriptors. *International Journal of Computer Vision*, 94(1):101–117, 2011.

[13] Edgar Roman-Rangel, Carlos Pallan Gayol, Jean-Marc Odobez, and Daniel Gatica-Perez. Searching the past: an improved shape descriptor to retrieve maya hieroglyphs. pages 163–172. ACM, 2011.

[14] John Eric Sidney Thompson and S. Eric. *A catalog of Maya hieroglyphs*. University of Oklahoma Press Norman, 1962.

[15] Gabrielle Vail and Christine Hernández. The Maya Codices Database, Version 4.1. *A Website and Database Available at: http://www. mayacodices. org/(accessed on 29.09. 13.)*, 2013.

[16] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-SNE. *Journal of Machine Learning Research*, 9(2579-2605):85, 2008.

[17] G. Zimmermann. *Die Hieroglyphen der Maya-Handschriften*. Abhandlungen aus dem Gebiet der Auslandskunde / Reihe B: Völkerkunde, Kulturgeschichte und Sprachen. De Gruyter, 1956.