Radboud University

Bachelor Thesis

B.Sc. Artificial Intelligence

Phonological and Visual Mapping of Letters of a Foreign Alphabet for Educational Software

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Abstract

Similarity coding is dominant in the human lexicon. The educational game MindSort is based on this idea and therefore constitutes a psychologically plausible game for learning vocabulary. Not only words, also letters are coded based on similarity. MindSort could therefore be extended to learning foreign alphabets if a distance measure for the letters is found. The present paper established a distance measure for the Indian script Devanagari by fitting phonological and visual features on similarity judgement data obtained by ten native Hindi-speakers. The analysis showed that for both sets of features, all but seven features constituted a significant contribution to the distance measure. An individual distance measure has also been found for each individual subject. For almost all subjects, the phonological features were a good explanation of their similarity judgements and for the visual features it was a good explanation for most of the participants. As the weights for the features varied per subject, an individual arrangement should be obtained from MindSort users after they familiarized themselves with the letters such that the game suits the individual learner's brain best.

Introduction

As our world is becoming more globalised, learning foreign languages becomes more and more important. It is hypothesized that language learning can be facilitated when it happens in a brain-inspired way. As similarity coding is dominant in the human brain (Edelmann, 1998), an example for such brain-inspired learning is to learn language concepts according to their similarity. The educational game MindSort uses this neuroscientific insight to help users learn words of a foreign language. Ideally, it could also be extended to learning letters of a foreign, non-Latin, alphabet. This paper therefore seeks to establish a distance measure for the letters of the Indian script Devanagari for both their phonological and the visual features.

In the course of globalisation, non-Western countries are emerging and learning non-European languages becomes important. In the list of the top ten most important foreign language identified by the British Council (2013), half of the languages are non-European of which four are not written in the Latin alphabet. Factors that have been considered were of various nature, including cultural, political and economic factors.

The clear importance of learning foreign languages asks for efficient ways for acquiring them. Neuroscientific and psycholinguistic research provides important insights into how language learning works and how it potentially can be made easier (de Jong et al., 2009). A well-established insight which can be used for learning language concepts is that similarity coding is dominant in the human brain.

The idea of similarity being fundamental to mental processes originated in Aristotle's principle of association by resemblance (Shepard, 1987). Yet, similarity effects have not been studied experimentally until Pavlov (1927) found that dogs do not only salivate at the sound of a bell on which they have been conditioned on, but also to sounds similar to it, with the salivation increasing with the degree of similarity. Since then, researchers have investigated the relation between learned responses and difference measures between a test stimulus and an original stimulus (Shepard, 1987).

Similarity coding is dominant in different domains of the brain. One prominent example is the mental lexicon: the collection of words which we store in our cognitive system and access in order to understand speech and written language (Acha & Carreiras 2014). Access to the the mental lexicon involves partially distinct processes for accessing orthography, phonology, and semantics (Miozzo, 2008), at all which levels similarity coding plays a potential role.

The lower-level access to the lexicon which precedes the semantic processing involves the access over a orthographic and phonological route (Acha & Carreiras 2014, Chastain, 1984). The importance of phonological information for lexical access has been shown using the lexical decision task, a task in which subjects judge whether a given string is a word or a nonword. Meyer, Schvaneveldt and Ruddy (1974) showed that reaction times in a lexical decision task were small for word pairs that were both visually and phonologically similar (e.g. FENCE-HENCE) but larger for words that were only visually similar but phonologically different (e.g. FREAK-BREAK). This effect of phonological similarity does not only indicate the importance of the phonological route to the lexicon,it also highlights the predominance of similarity within the phonological representation. More evidence for similarity coding can be found in similarity neighbourhood studies: Vitevitch (2002) found that more errors were produced in the spoken production of words which have a sparse phonological neighbourhood (i.e. only few similar sounding words exists) than for words with a dense neighbourhood. This shows that along with a target word, words of high phonological similarity get activated as well, increasing the accuracy of speech. It also implicates that these words must be located close to one another in the mental representation.

Before orthographic or phonological process can take place, single letters have to be recognized first. The scientific community has reached consensus over the past years that letter perception can be explained by a feature-based approach (see Grainger, Rey & Dufau, 2008, for a review): The letters' visual features have to be detected and are then matched with their representation in memory. According to the Pandemonium model for letter perception (Selfridge, 1959), feature detectors (detecting e.g. curves, lines) activate letter detectors, which again activate the 'master demon' that makes the final decision. When the features of different letters are similar, it is possible that a letter is recognized incorrectly. It is hypothesized that the rate at which letters are confused with one another reflect visual similarity based on their shared features (Grainger, Rey & Dufau, 2008). Courrieu, Farioli and Grainger (2004) measured reaction times that it took participants to discriminate between letters. They transformed the reaction times into Euclidean distances and verified that such metric can account for perceptual similarity. These findings suggest that similarity coding is dominant in the mental representation of letter shapes as well.

The educational software MindSort makes use of the theoretical knowledge about similarity coding in the brain and within the mental lexicon in particular. It is an educational serious game for learning new vocabulary which is based on the classical memory game: cards with the translation equivalent words have to be matched. These cards are arranged according to their similarity and therefore resemble the assumed structure of the mental representation. The idea behind this is that the brain-inspired arrangement facilitates word learning.

Not only words, also letters are probably stored according to similarity: both phonological and visual similarity. As stated above, learning non-Western languages becomes more important and most of them are not written in the Latin alphabet. Hence, the MindSort game could ideally be extended to learning foreign writing systems. To achieve this, a distance measure has to be found for both phonological and visual similarity.

Towards this end, the present paper seeks to answer the research question: What is the optimal distance measure to map letters of a foreign alphabet based on their phonological and visual features? The distance measure will be established for the Devanagari script by obtaining similarity judgements from native-Hindi speakers and fitting a set of phonological and visual features on the resulting data. Devanagari is an alphasyllabary[1] in which Indic languages such as Hindi, Sanskrit or Nepali are written. The letters in the alphabet are ordered according to the place of articulation

[1] For better readability I am going to refer to it as an alphabet from now on.

(Kachru, 2006). Hindi is the fourth-most spoken language in the world by first language speakers (British Council, 2013) and the Devanagari script is used by roughly half a billion people (Indira et al., 2012) making it an important script to learn in the mentioned globalizing world.

Methods

Participants

In order to answer the research question, similarity judgements were obtained from native Hindi speakers by letting them arrange letters in a 2D space on a computer. It was important to use native-speakers to ensure sufficient familiarity with the written letters and because non-natives would not be able to perceive the phonological difference between letters that do not cross a phonological boundary in their own language (Werker & Lalonde, 1988).

10 native Hindi-speakers between the age of 24 to 32 (average age 28) participated in the experiments, of whom four were male and six female. They all grew up with Hindi and another language: For six it was the main language they spoke while growing up and four spoke it equally often as their second native language (English, Punjabi or Gujarati). While all participants reported only reading Devanagari occasionally or seldom in their adult life, they all learned it in school starting at the age of four to seven and have all been reading in Devanagari daily while growing up. Furthermore, nine out of ten participants judge their Devanagari reading skills as good or very good. It can therefore be assumed that they are all capable of giving expert judgements on the given letters.

All the participants hold an academic degree, two hold a Bachelor's degree and the rest a Master's degree. Except of one participant who works in Marketing, all participants work in the STEM area or do their Ph.D. in this field.

Apparatus and Materials

The inverse MDS multi-arrangement method. For the experiments, the inverse multidimensional scaling (MDS) multi-arrangement method by Kriegeskorte and Mur (2012) was used. It enables subjects to arrange images of multiple items according to their similarity in a two- dimensional arena on a computer screen.

The MDS method assumes the geometrical model, which is based on the idea that dissimilarities can be represented as distances in space (Coombs, 1954). Therefore, a visualized 2D arrangement of items can be calculated from pairwise dissimilarities. For Inverse MDS, this process is inversed: it measures distances in the 2D arrangement and creates a matrix of pairwise dissimilarities.

The method consists of several trials in order to collect enough evidence for every similarity. The first trial consists of all items and gives a first estimate of the entire representational dissimilarity matrix (RDM). For subsequent trials, subsets of the complete item set are shown. The algorithm that chooses these subsets is adaptive: it keeps track of the current amount of evidence that has already been collected for each dissimilarity. It then selects those items into the new subset for which more evidence is needed the most (Kriegeskorte & Mur, 2012).

The multi-arrangement method is efficient because many judgements can be given at once and psychologically plausible because items are judged within a context (Kriegeskorte & Mur, 2012). Furthermore, Kriegeskorte and Mur validated the method by comparing it to conventional behavioural methods, which proved consistent. It therefore seems a suitable method to be used for the experiments for this paper. The Matlab code was provided by Kriegeskorte and has been adapted to suit the experiments, as described below.

Modifications for the experiments. In order to make the inverse MDS code suitable for the experiment, the code was adapted so that it was possible to have one part for phonological similarity and one for visual similarity. In both parts, pictures of the Devanagari letters were used as the items to be sorted. For the phonological part these could also be clicked on to hear the sound of the letter.

Stimuli. The Devanagari alphabet consists of 11 vowels and 33 consonants plus eight letters for loanwords. 40 letters were chosen as stimuli for the experiment. A few letters were not included in the set of items. These include variations of the sound 'na', as they are usually not distinctive (Kachru, 2006). Furthermore, there are a few letters that have the exact same form as another letter, just with a diacritical point behind or below them. These letters were left out as well, because first of all the visual similarity would not be of much interest and secondly because most of these letters are not used in original Hindi words, but only in loanwords from Urdu (Kachru, 2006). The last letter that was left out is the retroflex r, because it is pronounced as a sequence of 'r' and 'i' (Kachru, 2006), which makes the comparability to the other letters difficult.

Figure 1. Left: The independent vowel 'e' without a consonant. Middle: The consonant 'pa' without a vowel (the 'a' is inherent to every vowel). Right: the vowel 'e' occurring together with a consonant is written as a diacritical mark (red).

Vowels are denoted with diacritical marks if they occur after a consonant (see Figure 1, right) and with their independent letter form when they precede a consonant (Figure 1, left), which is usually the case at the beginning of a word (Sharma & Gupta, 2015). As the diacritical marks always go together with a consonant, their comparability is difficult. Therefore, the independent forms of the letters were used.

Procedure

After being informed about the experiment and filling in a consent form, the participants started with either the phonological part or the visual part, as the order was counterbalanced across subjects. For the phonological part they got headphones in order to be able to listen to the letters.

In every trial, the participants got to see the screen with the letters placed around the circular arena (Figure 2a). The participant could then drag-and-drop the letters into the circle with the mouse to create an arrangement (Figure 2b). In subsequent trials only a subset of letters was shown (Figure 2c). Test runs showed that no maximum number of items per trial was required to guarantee convergence within reasonable number of trials, so all letters were shown in the first trial.

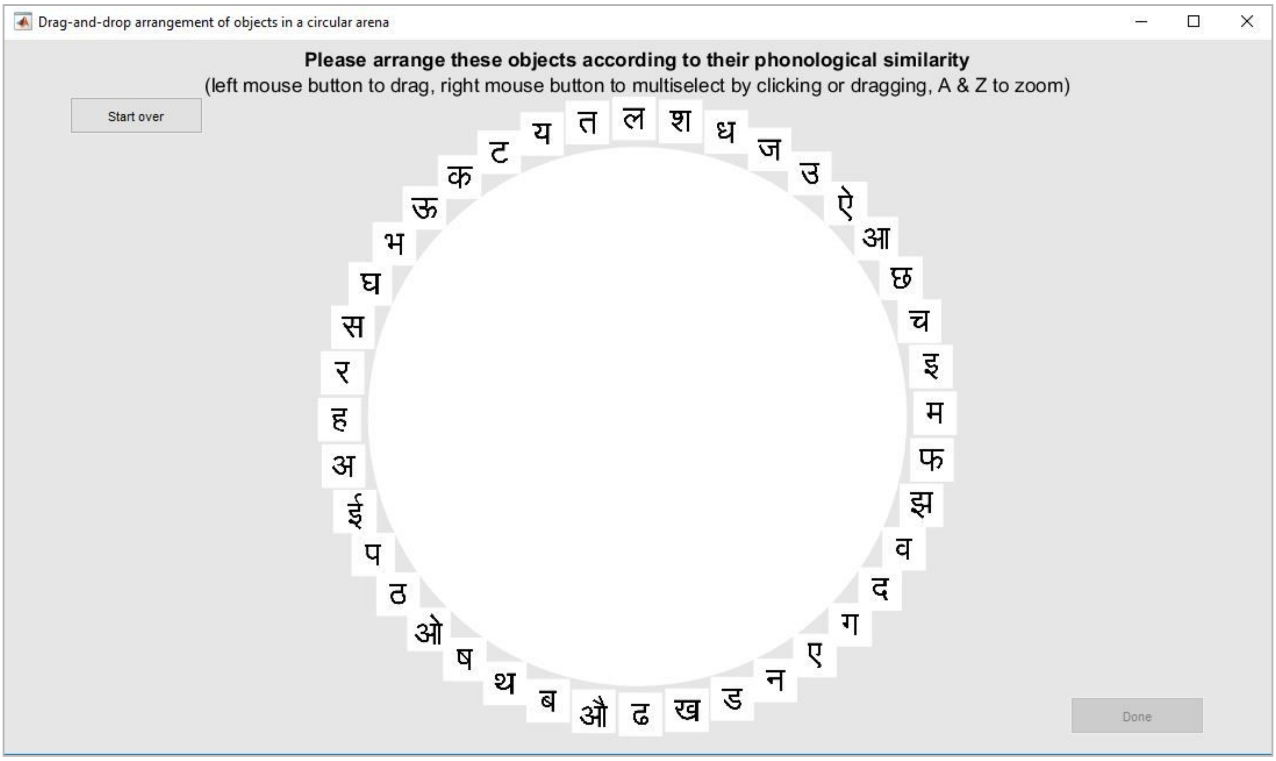


Figure 2a. The screen of the first trial with the complete set of letters, before sorting.

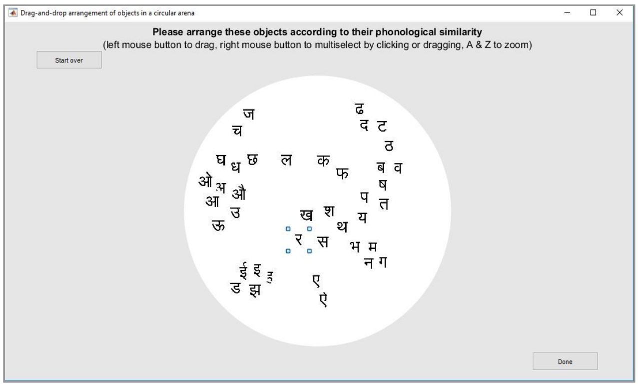


Figure 2b. The screen of the first trial with the complete set of letters, with an example sorting.

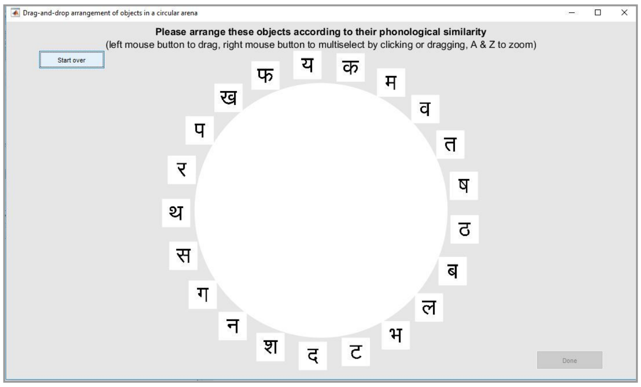


Figure 2c. The screen of a subsequent trial with a subset of the complete letter set.

The number of trials varied per subject as the programme determined how many trials were needed for a precise average. Test runs showed that no maximum number of items per trial was required to guarantee convergence within reasonable number of trials, so all letters were shown in the first trial. The first run was directly followed by the other (phonological or visual) run. At the end, the participants filled in a questionnaire about general demographic information and their language background. All participants took around an hour to finish the experiment.

Analysis

In order to find a suitable distance measure that models human judgement, phonological and visual elements were identified to be fitted on the judgement data obtained from the experiments. For determining the phonological distance, established phonological features were used. For the visual distance, existing classifications using common graphical elements and the position of the vertical bar were extended by a number of self-defined features. For every letter, it was established whether it contained this feature or not. This made it possible to create a similarity matrix in which the euclidean distance between the vectors of each letter pair was calculated.

In a second step, the optimal weights for each feature per subject were found by fitting the data using linear multiple regression. This fits a linear equation on the data in order to model the relationship between the predictor variables and the response variable, in this case between the established features and the human judgement data. The fitting results in coefficient estimates for the response variables, which gave each feature a weight.

Finally, the features were analysed over all subjects using a generalized linear regression model, in which the response variable does not have to follow a normal distribution. This was achieved by first creating a matrix of feature distance vectors per subject and then concatenating these matrices. Generalized linear regression was performed with the concatenated matrix as predictor variables and the human data in vector form as response variable.

As multiple significance tests were conducted for the analysis, there should usually be a correction for the multiple comparison problem. Given the low sensitivity (small amount of participants), this has not been done for the present study.

The phonological and visual features are described below. The complete feature tables can be found in the appendix (Appendix 1 for the phonological features, Appendix 2 for the visual features).

Phonological Features. For the analysis of the phonological similarities, thirty-one phonological features were chosen as a combination of features proposed by Ohala (1983) and Ohala & Ohala (1992) and were identified for each letter. The broader categories of these features include voicing, aspiration, place of articulation and manner of articulation (Harley, 2013).

Voicing refers to the use of the vocal cords: A consonant is voiced if the vocal cords are vibrating from the moment the lips are released and it is unvoiced if air can first pass between the vocal cords before closure. Aspirated consonants are created with a breadth of air being released when pronouncing a consonant. The place of articulation in the mouth can reach from consonants being articulated at the soft palate in the back of the mouth (velar consonants) towards sounds being produced with the lips (labial consonants). The manner of articulation concerns the constriction of airflow, for example in fricatives such as ‘sa’ where the constriction of airflow results in a hissing sound (Harley, 2013).

Visual Features. As visual features, classifications by Bhagwat and by Naik (1971) were combined with a number of self-defined features. Bhagwat was the first who established a graphical classification of the Devanagari alphabet according to the letter's similarity (Sharma & Gupta, 2015). He grouped letters together that share a common graphical element (see Figure 3). For some groups, he put one or two letters between parentheses. In these cases, two features were used in the analysis, one with the alternative letters included and one without. Some groups mainly consisted of letters that were not included in the set of stimuli and were therefore left out.

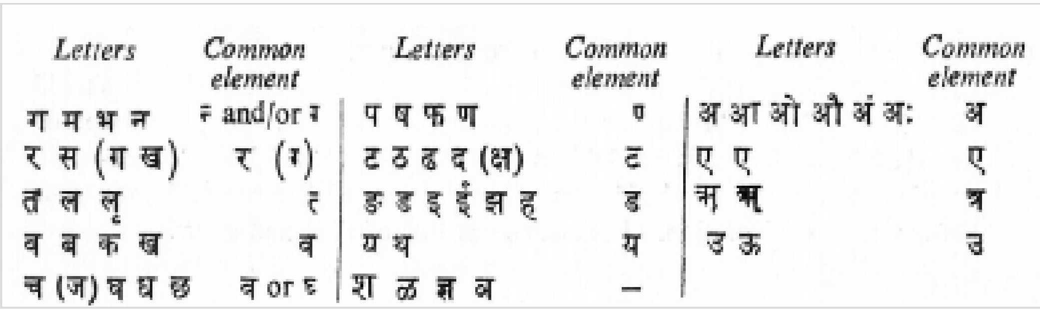


Figure 3. Bhagwat’s grouping of letters according to common graphical elements (Figure taken from Naik, 1971). Names: 1st row: Na, Ga, Na/Ga; 2nd row: ra, ra-variant, 3rd: ta; 4th: va, 5th: ghava, ghava-variant; 6th: not included; 7th: tta, 8th: da, 9th: ya; 10th: not included; 11th: a 12th: e, 13th: not included; 14th: u.

Another attempt for a classification of the letters has been made by Bapurao Naik (1971), who grouped the letters in five groups according to the position of the vertical bar (see Figure 4).

	Vowels	Consonants	
Group 1	letters	with full verti-bar *attached* (अंत्यदंडयुक्त)	20
	अ	ख घ च ज झ त थ ध न प ब भ म य व ष स क्ष ज्ञ	
Group 2	letters	with full verti-bar *detached* (अंत्यदंडयुक्त)	3
		ग ण श	
Group 3	letters	with a short-bar (अल्पदंडयुक्त)	14
	उ ऊ ऌ ॡ	ङ छ ट ठ ड ढ द ल ह ळ	
Group 4	letters	with a central-bar (मध्यदंडयुक्त)	4
	ऋ ॠ	क फ	
Group 5	letter	without a bar (दंडरहित)	1
		र	

Figure 4. *Naik's (1971) grouping of letters based on the position of the vertical bar.*

Both classifications were taken over for the visual feature table. They were extended by nine self-defined features (Figure 5).

Nr.	Full name/description	Common element	Letters
1	Oblique line of 'ra' in the lower left. (र)	\	र ए ऐ स
2	Arc of 'ya' (य)		य थ ख
3	Horizontal line with corner pointing down on the left		न त
4	Empty square	□	स भ म
5	Ending in a circle-like loop		छ द

Nr.	Full name/description	Common element	Letters
6,7	Three-shaped	3	अ आ ओ औ उ ऊ (ध छ घ)
8	Two-shaped	2	भ श थ
9	Horizontal letter attached to the vertical bar		न ज च

Figure 5. *The self-defined features.*

For the first eight, the notion of common graphical elements was taken as inspiration. The first three share the exact same element: the oblique line of the letter 'ra' (Feature 1), the arc of the letter 'ya'(Feature 2) and a horizontal line with a downward-pointing corner on the left (Feature 3).

Feature 4 to 8 are similar-looking elements rather than exactly the same elements. Feature 4 is an empty square, which is completely closed for two, but slightly open for one letter. Feature 5 can be found in two letters which both end in a circle-like loop, where the position of this loop is slightly different for both letters. Feature 6 and 8 resemble the shape of the Arabic numbers 2 and 3, respectively, with their round arcs differing in length and being tilted to different degrees. Feature 7 is an alternative version of Feature 6, which includes letters that resemble a three mirrored on the vertical axis. Similarly to the alternative letters of Bhagwat, these were used as two separate features in the analysis. Finally, the ninth feature is closer to the approach of Naik: it groups together three letters of horizontal shape which are horizontally attached to the vertical bar.

Summary of the Features. For the phonological features, thirty established phonological features were used such as place and manner of articulation. For the visual features twenty-nine features were used which were a combination of the classification of Bhagwat using common graphical elements, of Naik (1971) using the position of the vertical bar and a set of self-defined features.

Results

In order to obtain a distance measure for the Devanagari letters, weights had to be found for the established phonological and visual features. The feature weights per subject were found using a linear regression model. In addition to that, R^2 values were calculated for all subject as a measure of how well the weighted features can explain the judgment data. In an analysis over all subjects using a generalized linear model, it was determined which features have a significant feature weight. In the following, the results of this analysis will be discussed.

The number of trials for both runs (phonological and visual) varied between the participants, as the programme calculated how many trials were needed for sufficient evidence. One participant had an exceptional high number of total trials (57), while for the rest the average was 14 trials (ranging from 5 to 24).

Results Phonological Features

The data per subject was analysed using a linear regression model, which fitted a linear equation on the observed data and resulted in weights for each subject in the form of coefficient estimates. The analysis revealed that the weighted phonological features were a significantly better fit for the phonological data than a constant model: For all subjects the F-test of overall significance yielded significant results ($p<0.01$). The percentage of variability in the human data that was explained by the weighted features (measured in R^2) varied per subject. Half of the participants had a high R^2 value ranging from 0.44 to 0.59, three had a medium high value ranging from 0.21 to 0.34 and two participants had low values of 0.12 and 0.05 (see Figure 6).

Figure 7 shows that some feature weights varied considerably between the participants, while other weights showed less variability. The individual weights range from -0.35 to 0.48 and the weight average per feature ranged between -0.4 and 0.25. A table with all weights per feature and subject can be found in the appendix (Appendix 3 for the phonological features, Appendix 4 for the visual features).

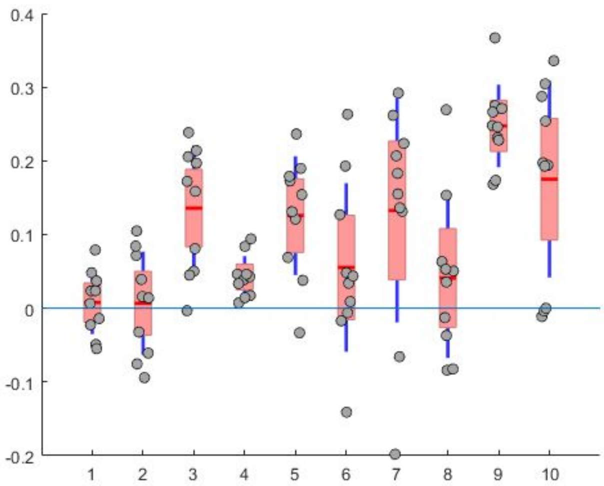
Subject Nr.	RSquare	F	p	Estimate Error Variance
01.	0.25	35.8679	< 0.01	0.065
02.	0.59	87.1449	< 0.01	0.035
03.	0.44	52.4347	< 0.01	0.049
04.	0.21	32.6770	< 0.01	0.069
05.	0.12	24.7708	< 0.01	0.077
06.	0.59	87.1449	< 0.01	0.036
07.	0.48	62.2253	< 0.01	0.045
08.	0.05	24.7564	< 0.01	0.083
09.	0.57	76.3067	< 0.01	0.038
10.	0.34	39.5168	< 0.01	0.057

Figure 6. Statistics (R^2, F, p, Estimate of Error Variance) from the multiple linear regression per subject for the phonological features.

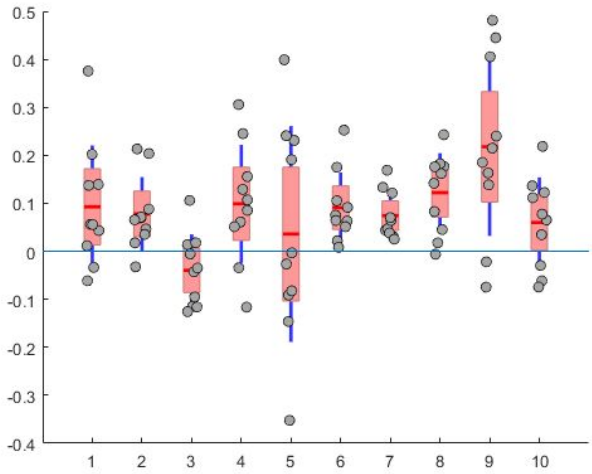
The general linear regression model over all subjects revealed that all but seven features were statistically significant ($p<0.05$). In the group manner of articulation all but two features were significant and for features concerning the place of articulation only one was non-significant. Despite the remaining group of features having the most non-significant features, it also contains the most important feature ‘consonantal’ (weight=0.18). The three most important features after ‘consonantal’ with a significant weight above 0.1 were ‘flap’ (0.17), ‘velar’ (0.14), and ‘lateral’ (0.12).

Also over all subjects the model was a better fit than a constant model (F-statistic vs. constant model: 85.9, p-value <0,01). The R^2 value was 0.18.

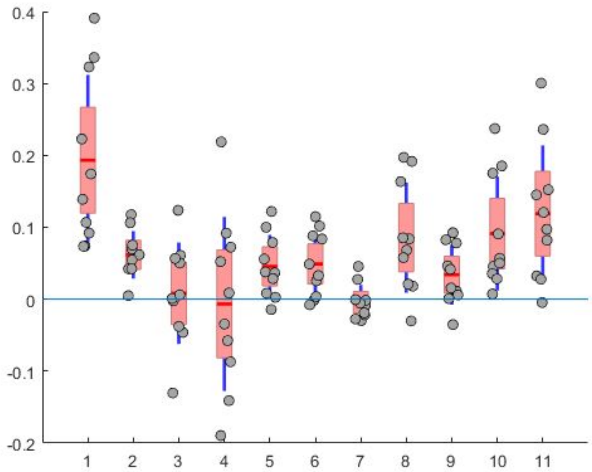
7a)



7b)



7c)



Manner of articulation:	**Place of articulation:**	**Other:**
1. sonorant	1. labial	1. consontantal
2. continuant	2. coronal	2. voice
3. approximant	3. dorsal	3. anterior
4. aspirated	4. bilabilal	4. back (cons.)
5. nasal	5. labidental	5. high
6. plosive	6. dental	6. low
7. friccative	7.retrofelx	7. long
8. affricative	8. palatal	8. back(vow.)
9. flap	9. velar	9. mid
10. lateral	10. glottal	10. front
		11. central

Figure 7 a-c. Weights for the phonological features (manner of articulation, place of articulation, others). Grey dot: weight of one participant. Red line: average weight for that feature. Red Box: 1.96 Standard Error of the Mean, SEM (95% confidence interval). Blue line: on standard-deviation. Plotted using Campbell (2017).

Results Visual Features

The F-test of overall significance yielded similar results to those of the phonological feature analysis: The results for all subjects were significant ($p < 0.01$), so the weighted features were again a significantly better fit for the data than a constant model.

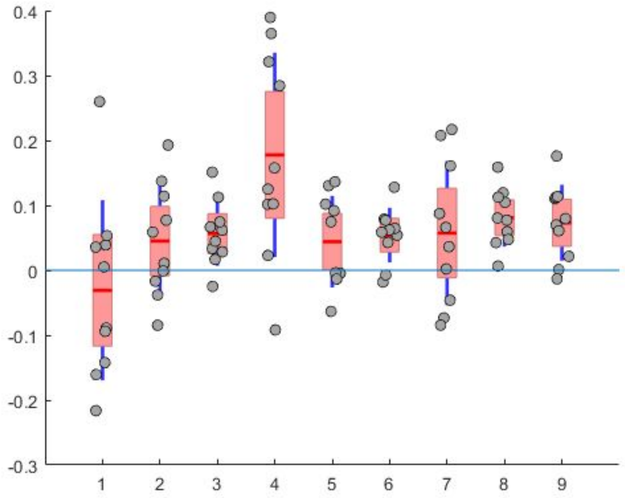
Subject Nr.	RSquare	F	p	Estimate Error Variance
01.	0.12	31.0441	< 0.01	0.077
02.	0.23	32.0296	< 0.01	0.067
03.	0.18	35.2149	< 0.01	0.071
04.	0.15	29.3428	< 0.01	0.074
05.	0.27	40.9050	< 0.01	0.063
06.	0.48	69.0897	< 0.01	0.046
07.	0.40	52.2936	< 0.01	0.053
08.	0.01	24.2805	< 0.01	0.086
09.	0.47	67.6483	< 0.01	0.046
10.	0.22	31.7624	< 0.01	0.068

Figure 8. *Statistics (R^2, F, p, Estimate of Error Variance) from the multiple linear regression per subject for the visual features.*

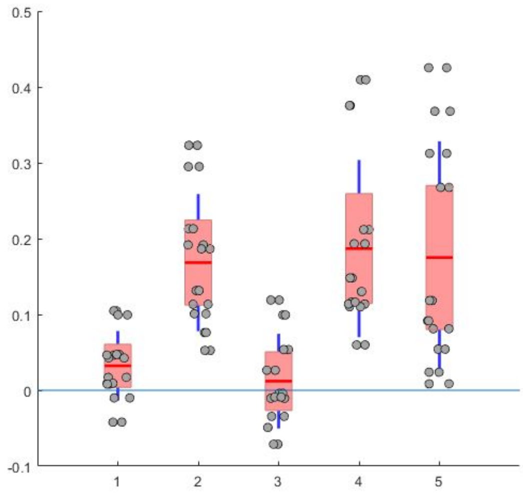
The R^2 values show, however, that the visual features can explain the variability in the human visual data slightly worse than the phonological features could explain the phonological data. For four participants the R^2 value was under 0.2 and for another three the value was below 0.3. Three participants, however, did have a high value between 0.40 and 0.48.

Figures 9a-c show that, again, some feature weight showed more variability across participants than others. For Bhagwat's features, the weights ranged from -0.14 to 0.49 and the average weights per feature varied between 0 and 0.32. The weights of Naik's feature ranged from -0.07 to to 0.43, with average weights between 0.17 and 0.19. For the self-defined features, the lowest weight was -0.22 and the highest 0.39. The average lay between -0.03 and 0.39.

9a)



9b)



9c)

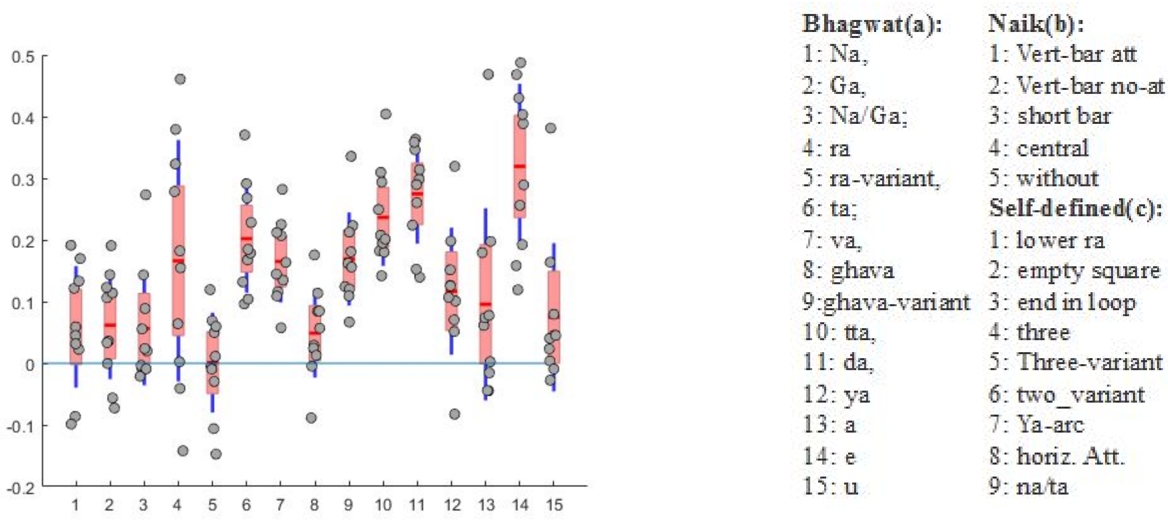


Figure 9a-c. Weights for the visual features for the features of Bhagwat(a), Naik(b), and the self-defined features(c). Grey dot: weight of one participant. Red line: average weight for that feature. Blue vertical line: reference line at zero. Red Box: 1.96 Standard Error of the Mean, SEM (95% confidence interval). Blue line: on standard-deviation.Plotted using Campbell (2017).

The general linear regression model over all subjects showed that all but seven visual feature were significant ($p<0.05$). For Bhagwat's features, ten out of fifteen were significant and for Naik's features and the self-defined features all but one were significant.

The features with significant weights had stronger weights than the phonological features had. While there were only four phonological features with a weight higher than 0.1, nine visual features were above it. The most important visual features were 'tta', 'da' 'e' (Bhagwat's features), and 'three-shaped'(self-defined feature).

The average weight of Bhagwat's features was 0.073, for Naik's features it was 0.068 and for the self-defined features 0.038.

Again, 63.2 over all subjects the model was a better fit than a constant model (F-statistic vs. constant model: 85.9, p-value <0,01). The R^2 value was 0.13.

Discussion

The aim of the study was to establish a suitable distance measure for the letters of the Devanagari alphabet. This has been achieved by collecting similarity judgement data of ten native Hindi speakers and fitting models of phonological and visual features to it. The resulting feature weights form the distance measure for every participant. The analysis per subjects shows that for all participants, the weighted features are a better fit for the similarity judgements than a constant model, for both the visual and the phonological part. This indicates that weighted features are indeed a suitable approach for the distance measure.

Moreover, the analysis per subject shows that the weighted phonological features provide a reasonably good explanation for how the native-speakers have arranged the letters. The weighted visual features, seem to be a good explanation for most participants, but for some it can only partially explain the mechanisms underlying the similarity judgements. An explanation for this might be that the participants are more aware of the phonological characteristics of the letters because they are already grouped according to the place of articulation in the alphabet. Focussing attention on the graphical characteristics, on the other hand, is not something adult native-speakers naturally do once they acquired reading fluency.

Nevertheless, the analysis of the features over all subjects shows that all but seven features are significant, both for the visual and the phonological features. Given the non-significance of the remaining features, these can be left out of the distance measure.

A possible explanation for the non-significance is that it is caused by a strong overlap with other features. For the features ‘ga’ and ‘na’, for example, there is also the feature ‘naga’ which combines the two. While the common graphical elements of the two features might have been important, the combined feature already explains the data better. Similarly the ‘ra-variant’ and ‘gha-variant’ are extensions of the ‘ra’ and ‘ga’ feature and cannot add significant information. Given their non-significance, these features can be left out of the distance measure.

The remaining features are a meaningful model of the dissimilarity between the Devanagari letters. Especially meaningful are the features with a high weight, which are more frequent for the visual features. This indicates that giving weights to the features has an even stronger impact for the visual features, emphasizing the importance for a weighted feature approach.

For the visual features, the average weight is highest for the features of Bhagwat and lowest for the self-defined features. The fact that also three of the strongest features are features of Bhagwat also indicates that his features are the most important ones. Given that there are high significant weights in the other two feature sets as well, it can nonetheless be concluded that all three sets of features (without the non-significant ones) are meaningful for the model and should be included in the distance measure.

The weights resulting from the analysis over all subjects could be used as a general distance measure to be implemented in the MindSort game. However, the differences in weights and in R^2 values show that the representation of the letters is different for different people and the arrangement for MindSort should be individualized as well. When complete beginners start playing the game, this will not be possible yet, because they will not be familiar with the visual shape of the letters and will not yet be able to distinguish between letters that do not cross a phonological boundary in their own language (Werker & Lalonde, 1988). A possible solution is to first start with an arrangement based on the general distance measure from the analysis over all subjects until the learners are fairly acquainted with the letters. Then, they can be asked to give their own personal arrangement with which the game is then played in all following rounds of the game.

When an individual arrangement is given, it can be expected to optimally represent the organization of the letters in the user's mind. The arrangement reflects the dominance of similarity coding in the human brain, both for phonology in the human lexicon and for the storage of letters shapes in memory.

This places the present study within the research about similarity coding in the human mind and gives an example of how such neuroscientific findings can be used to facilitate learning through educational software. Besides that, the study confirmed the importance of existing phonological features for perceived similarity and offers new insights about relevant visual features of the Devanagari letters.

Limitations

The proposed distance measure gives a reasonably good explanation for the similarity judgements of the native speakers. The R^2 values were, however, not equally high for all participants and in general lower for the visual features. This might stem from possible difficulties with the method of obtaining similarity judgements.

First and foremost, the task of giving a holistic arrangement of all letters is quite a difficult one. While observing the participants carrying out the experiment, it could be seen that the majority of participants grouped similar letters in clusters and focussed on within-cluster similarities, while between-cluster distances didn't seem to be taken into consideration as much. Kriegeskorte and Mur (2012) discuss the problem of participants focussing on local relationships rather than global relationships as well.

Another problem was that most participants had at least a few letters that they grouped inconsistently over the different trials, probably because it was difficult to attend to all the letters or because their perception changed within a different context. In general the adaptive algorithm that chooses the new subsets should take care of this and continue showing the letters in a new trial until enough evidence has been collected for the similarity. If participants continuously group one letter with different other letters every trial, however, this will distort the general results nonetheless. One of the participants seem to have given particularly inconsistent judgements, as she had to do a considerably higher amount of trials.

Two more problems arose from the difficulty of judging the virtual distance between items on the arena. Firstly, a lot of subjects tended to arrange similar objects in a row instead of a group. This results in the first and last item of the row to be much further apart than the letter of another cluster. While for the human eye, the clusters are visually clear, they are not measurable by calculating actual distances. The second issue was that some letters were considered not to be similar to any letter at all. The participants than tried to put these letters somewhere close to the border of the circle. In this position, however, the distances to other clusters were not actually that high, because there wasn't enough space left in the arena.

Future research

As there are some limitations to the current findings as listed above, more research is needed to validate the findings and establish a reliable mapping of letter. For example, the issue of participants having focussed on local within-cluster relationships could be overcome by another experiment where subjects have to judge between-cluster relationships only.

Furthermore, it might be interesting to repeat the experiments of the present study with a more diverse participants group. The participants for this study have been relatively homogeneous with regard to age, level of education, and occupational/academic background. Also, all participants have not have had as much contact with Devanagari and written Hindi since living abroad in the Netherlands. It could therefore make the results more generalizable if the experiments were repeated with Indians living in India or with subjects with a different background. Especially people with a background in either language studies or art and design could be interesting, because they might have “a better eye” or “a better ear” for visual and phonological aspects of a letter, respectively. It could also be considered doing the visual part of the experiments with intermediate learners of the alphabet, as they had to give special attention to visual elements of the letters while studying them and can be expected to have a greater awareness of their visual features than native-speakers who automatized the letter identification process a long time ago.

After a reliable, holistic arrangement has been established, further research is needed to test the learning facilitation effect when such an arrangement is used for the MindSort software as opposed to a random arrangement. As such it can be established whether learning is indeed made easier when the items to be learned are presented in the same way they are organized in the brain.

As the arrangement of letters for the MindSort-user should be personalized, the data of the present study could be re-analyzed to find out whether it is enough to let the user arrange a subset of the letters. This subset would then constitutes a training set for which the feature weights are calculated and which could possibly predict the weights for the remaining data.

Conclusion

The present study has established a general distance measure for the Devanagari letters based on an analysis over all subjects as well as individual distance measures for each participant. The individual analyses show that the weights and R^2 values vary per participant and therefore a personalized arrangement should be obtained from the MindSort users after they acquired a certain familiarity with the letters.

When this is achieved, the letters can be learned using MindSort in a brain-friendly and therefore assumingly more effective manner: The arrangement of the letters is based on similarity and therefore represents the organization of the letters in the human mind, where similarity coding is dominant.

The study has focused on the letters of the Devanagari alphabet. Other languages and their writing systems, such as Chinese, Arabic or Russian can be expected to be of high importance in the future (cf. British Council, 2013). Therefore, it would be valuable for the MindSort application to establish mappings for these languages as well. As such, MindSort can become an important tool for learning not only words but also foreign alphabets in a psychologically plausible way.

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Appendix 1 Phonological Feature Table

Manner of articulation

	consonantal	sonorant	continuant	approximant	aspirated	nasal
a'	0	1	0	0	0	0
aa'	0	1	0	0	0	0
ai'	0	1	0	0	0	0
au'	0	1	0	0	0	0
ba'	1	0	0	0	0	0
bha'	1	0	0	0	1	0
ca'	1	0	0	0	0	0
cha'	1	0	0	0	1	0
da'	1	0	0	0	0	0
dda'	1	0	0	0	0	0
ddha'	1	0	0	0	1	0
dha'	1	0	0	0	1	0
e'	0	1	0	0	0	0
ga'	1	0	0	0	0	0
gha'	1	0	0	0	1	0
ha'	1	0	0	1	0	0
i'	0	1	0	0	0	0
ii'	0	1	0	0	0	0
ja'	1	0	0	0	0	0
jha'	1	0	0	0	1	0
ka'	1	0	0	0	0	0
kha'	1	0	0	0	1	0
la'	1	1	1	0	0	0
ma'	1	1	0	0	0	1
na'	1	1	0	0	0	1
o'	0	1	0	0	0	0
pa'	1	0	0	0	0	0
pha'	1	0	0	0	1	0
ra'	1	1	0	0	0	0
sa'	1	0	1	0	0	0
sha'	1	0	1	0	0	0
ssa'	1	0	1	0	0	0
ta'	1	0	0	0	0	0
tha'	1	0	0	0	1	0
tta'	1	0	0	0	0	0
ttha'	1	0	0	0	1	0
u'	0	1	0	0	0	0
uu'	0	1	0	0	0	0
ya'	1	1	1	1	0	0
va'	1	1	1	1	0	0

Appendix 1 Phonological Feature Table

					place of articulation general	
plosive	friccative	affricative	flap	lateral	labial	coronal
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	1	0
0	0	0	0	0	1	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
1	0	0	0	0	0	1
1	0	0	0	0	0	1
1	0	0	0	0	0	1
1	0	0	0	0	0	1
0	0	0	0	0	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
0	0	0	0	1	0	0
0	0	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	1	0
0	0	0	0	0	1	0
0	0	0	1	0	0	0
0	1	0	0	0	0	1
0	1	0	0	0	0	0
0	1	0	0	0	0	0
1	0	0	0	0	0	1
1	0	0	0	0	0	1
1	0	0	0	0	0	1
1	0	0	0	0	0	1
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	1	0

Appendix 1 Phonological Feature Table

	place precise					
dorsal	bilabial	labiodental	dental	retroflex	palatal	velar
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	1	0	0	0	0	0
1	0	0	0	0	1	0
1	0	0	0	0	1	0
0	0	0	1	0	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0
1	0	0	0	0	0	1
1	0	0	0	0	0	1
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
1	0	0	0	0	1	0
1	0	0	0	0	1	0
1	0	0	0	0	0	1
1	0	0	0	0	0	1
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
1	0	0	0	0	1	0
0	0	0	0	1	0	0
0	0	0	1	0	0	0
0	0	0	1	0	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
1	0	0	0	0	1	0
0	0	1	0	0	0	0

Appendix 1 Phonological Feature Table

	others					vowels only
glottal	voice	anterior	back conso.	high	low	long
0	0	0	0	0	1	0
0	0	0	0	0	1	1
0	0	0	0	0	1	1
0	0	0	0	0	1	1
0	1	0	0	0	0	0
0	1	0	0	0	0	0
0	1	0	0	1	0	0
0	1	0	0	1	0	0
0	1	1	0	0	0	0
0	1	1	0	0	0	0
0	1	1	0	0	0	0
0	1	1	0	0	0	0
0	0	0	0	0	0	1
0	1	0	1	1	0	0
0	1	0	1	1	0	0
1	1	0	0	0	1	0
0	0	0	0	1	0	0
0	0	0	0	1	0	1
0	1	0	0	1	0	0
0	1	0	0	1	0	0
0	0	0	1	1	0	0
0	0	0	1	1	0	0
1	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	1
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	1
0	0	0	0	1	0	0
0	0	1	1	1	0	0
+	+				+	

Appendix 1 Phonological Feature Table

vowel back	mid	front	central
0	0	0	1
0	0	0	1
0	0	1	0
1	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	1	1	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	1	0
0	0	1	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
1	1	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
1	0	0	0
1	0	0	0
0	0	0	0
0	0	0	0

Appendix 2 Visual Feature Table

	Bhagwat na	ga	ga/na	ra	ra_variant	ta
a	0	0	0	0	0	0
aa	0	0	0	0	0	0
ai	0	0	0	0	0	0
au	0	0	0	0	0	0
ba	0	0	0	0	0	0
bha	1	1	1	0	0	0
ca	0	0	0	0	0	0
cha	0	0	0	0	0	0
da	0	0	0	0	0	0
dda	0	0	0	0	0	0
ddha	0	0	0	0	0	0
dha	0	0	0	0	0	0
e	0	0	0	0	0	0
ga	0	1	1	0	1	0
gha	0	0	0	0	0	0
ha	0	0	0	0	0	0
i	0	0	0	0	0	0
ii	0	0	0	0	0	0
ja	0	0	0	0	0	0
jha	0	0	0	0	0	0
ka	0	0	0	0	0	0
kha	0	0	0	0	1	0
la	0	0	0	0	0	1
ma	1	1	1	0	0	0
na	1	0	1	0	0	0
o	0	0	0	0	0	0
pa	0	0	0	0	0	0
pha	0	0	0	0	0	0
ra	0	0	0	1	1	0
sa	0	0	0	1	1	0
sha	0	0	0	0	0	0
ssa	0	0	0	0	0	0
ta	0	0	0	0	0	1
tha	0	0	0	0	0	0
tta	0	0	0	0	0	0
ttha	0	0	0	0	0	0
u	0	0	0	0	0	0
uu	0	0	0	0	0	0
ya	0	0	0	0	0	0
va	0	0	0	0	0	0

Appendix 2 Visual Feature Table

va	gha/va	gha/va_varian	tta	da	ya	a
0	0	0	0	0	0	1
0	0	0	0	0	0	1
0	0	0	0	0	0	0
0	0	0	0	0	0	1
1	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	1	0	0	0	0
0	1	1	0	0	0	0
0	0	0	1	0	0	0
0	0	0	0	1	0	0
0	0	0	1	0	0	0
0	1	1	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	1	1	0	0	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	0	1	0	0	0	0
0	0	0	0	1	0	0
1	0	0	0	0	0	0
1	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	1
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	1	0
0	0	0	1	0	0	0
0	0	0	1	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	1	0
1	0	0	0	0	0	0

Appendix 2 Visual Feature Table

e	u	Naik Vert-bar att	Vert-bar no-at	short bar	central	without
0	0	1	0	0	0	0
0	0	1	0	0	0	0
1	0	0	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	0	1	0	0	0	0
1	0	0	0	0	0	0
0	0	0	1	0	0	0
0	0	1	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	1	0	0
0	0	0	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	0	0	0	1	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	0	0	0	1	0
0	0	0	0	0	0	1
0	0	1	0	0	0	0
0	0	0	1	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0
0	0	0	0	1	0	0
0	0	0	0	1	0	0
0	1	0	0	0	0	0
0	1	0	0	0	0	0
0	0	1	0	0	0	0
0	0	1	0	0	0	0

Appendix 2 Visual Feature Table

Self-defined features

lower ra	empty square	end in loop	three	Three-variant	two_variant	Ya-arc
0	0	0	1	1	0	0
0	0	0	1	1	0	0
1	0	0	0	0	0	0
0	0	0	1	1	0	0
0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	1	0	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	1	0	0	0	0
0	0	0	0	1	0	0
1	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	1
0	0	0	0	0	0	0
0	1	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	1	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
1	0	0	0	0	0	0
1	1	0	0	0	0	0
0	0	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	0	0	1	1
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	0	0	1	1	0	0
0	0	0	1	1	0	0
0	0	0	0	0	0	1
0	0	0	0	0	0	0

Appendix 2 Visual Feature Table

horizontal atta	na/ta
0	0
0	0
0	0
0	0
0	0
0	0
1	0
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	0
1	0
0	0
0	0
0	0
1	0
0	0
1	1
0	0
0	0
0	0
0	0
0	0
0	0
0	0
0	1
0	0
0	0
0	0
0	0
0	0
0	0
0	0

Appendix 3 Phonological Feature Weights

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6
consonantal	0,17	0,10	0,32	0,13	0,22	0,39
sonorant	0,01	0,05	-0,02	0,04	-0,05	0,02
continuant	-0,08	0,04	-0,09	0,02	0,07	-0,03
approximant	0,21	0,05	0,04	0,08	0,21	0,19
aspirated	0,05	0,04	0,04	0,04	0,08	0,01
nasal	0,17	0,24	0,07	-0,03	0,19	0,15
plosive	0,05	-0,01	0,01	0,13	0,03	-0,14
friccative	0,22	-0,07	0,21	0,13	0,18	0,16
affricative	0,05	-0,04	0,06	-0,08	-0,01	0,15
flap	0,17	0,27	0,25	0,25	0,37	0,17
lateral	0,25	0,34	0,20	0,19	-0,01	0,30
labial	-0,06	0,01	-0,03	0,14	0,04	0,38
coronal	-0,03	0,07	0,21	0,02	0,09	0,07
dorsal	-0,10	-0,04	-0,11	0,01	0,02	-0,13
bilabial	0,31	0,25	0,09	0,11	0,13	-0,03
labiodental	0,19	0,23	0,24	-0,09	-0,03	-0,15
dental	0,02	0,18	0,11	0,08	0,09	0,06
retroflex	0,04	0,13	0,05	0,03	0,12	0,06
palatal	0,18	0,16	0,24	0,05	0,08	0,18
velar	0,21	0,14	0,48	-0,07	0,19	0,41
glottal	0,14	-0,06	0,12	0,07	0,11	-0,07
voice	0,04	0,12	0,06	0,07	0,11	0,04
anterior	0,00	0,06	0,00	0,05	-0,05	0,06
back conso.	0,09	0,05	-0,14	0,07	0,01	-0,03
high	0,12	-0,01	0,04	0,06	0,01	0,04
low	0,03	0,10	0,00	0,08	-0,01	0,09
long	-0,03	-0,01	0,00	-0,02	0,05	-0,01
vowel back	0,07	0,02	0,08	0,20	0,06	-0,03
mid	0,01	0,09	0,01	0,08	-0,04	0,00
front	0,19	0,06	0,05	0,24	0,04	0,05
central	0,15	0,12	0,15	0,03	0,08	0,00

Appendix 3 Phonological Feature Weights

	Subject 7	Subject 8	Subject 9	Subject 9
consonantal	0,07	0,09	0,33	0,07
sonorant	0,08	-0,01	-0,06	0,02
continuant	-0,06	0,08	0,01	0,10
approximant	0,16	0,17	0,00	0,24
aspirated	0,03	0,09	0,01	0,01
nasal	0,04	0,12	0,13	0,18
plosive	-0,02	0,04	0,26	0,19
friccative	0,14	-0,20	0,26	0,29
affricative	-0,08	0,04	0,27	0,05
flap	0,23	0,27	0,23	0,27
lateral	0,29	0,19	0,00	0,12
labial	0,20	0,06	0,06	0,14
coronal	0,20	0,05	0,07	0,04
dorsal	0,11	-0,03	-0,12	-0,01
bilabial	-0,12	0,06	0,16	0,05
labiodental	-0,35	-0,08	0,40	0,00
dental	0,05	0,25	0,06	0,01
retroflex	0,04	0,17	0,07	0,03
palatal	0,02	0,14	0,18	-0,01
velar	-0,02	0,24	0,44	0,16
glottal	-0,03	0,08	0,22	0,03
voice	0,05	0,04	0,00	0,08
anterior	0,12	0,01	-0,13	-0,04
back conso.	0,22	-0,06	-0,19	-0,09
high	0,00	0,08	0,03	0,10
low	0,11	0,05	0,03	0,00
long	-0,02	0,00	-0,03	0,03
vowel back	0,19	0,02	0,09	0,16
mid	0,08	0,05	0,02	0,04
front	0,09	0,18	0,01	0,03
central	0,30	0,10	0,03	0,24

Appendix 4 Visual Feature Weights

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6
na	0,17	0,19	0,06	-0,09	0,05	0,02
ga	0,11	0,11	0,14	0,12	0,04	0,19
ga/na	-0,01	0,02	0,00	0,06	-0,02	0,09
ra	-0,04	0,46	0,18	-0,14	0,32	0,15
ra_variant	0,07	-0,03	0,01	-0,01	0,05	-0,01
ta	0,17	0,27	0,18	0,10	0,37	0,13
va	0,23	0,28	0,21	0,13	0,06	0,16
gha/va	0,03	0,18	0,02	0,08	0,01	0,11
gha/va_varian	0,34	0,12	0,07	0,12	0,22	0,11
tta	0,14	0,18	0,18	0,31	0,25	0,40
da	0,14	0,15	0,30	0,31	0,26	0,22
ya	0,32	0,20	0,10	0,13	0,05	0,13
a	-0,04	0,00	0,06	-0,04	0,07	0,08
e	0,26	0,29	0,49	0,16	0,47	0,43
u	0,05	0,04	0,00	0,16	0,05	-0,01
Vert-bar att	0,05	0,02	-0,01	0,10	0,01	0,01
Vert-bar no-at	0,19	0,29	0,19	0,05	0,11	0,13
short bar	-0,01	0,03	-0,05	0,00	-0,01	0,12
central	0,21	0,11	0,06	0,11	0,41	0,12
without	0,27	0,02	0,08	0,43	0,05	0,09
lower ra	0,04	-0,16	-0,09	0,04	-0,22	-0,14
empty square	0,01	-0,02	0,11	0,19	0,08	0,06
end in loop	0,03	0,02	0,15	0,07	0,06	0,03
three	0,16	0,32	0,28	0,12	0,36	0,39
Three-variant	0,10	-0,01	0,13	0,09	0,00	-0,06
two_variant	-0,02	0,05	0,08	0,08	0,06	0,06
Ya-arc	-0,05	0,07	0,00	0,04	0,09	-0,07
horiz. Att.	0,08	0,04	0,12	0,06	0,05	0,10
na/ta	0,11	0,11	0,07	0,18	0,06	0,00

Appendix 4 Visual Feature Weights

	Subject 7	Subject 8	Subject 9	Subject 10
na	0,12	0,13	0,03	-0,10
ga	0,03	-0,06	0,00	-0,07
ga/na	-0,01	0,02	0,14	0,27
ra	0,38	0,28	0,00	0,06
ra_variant	-0,15	0,06	0,12	-0,11
ta	0,23	0,10	0,29	0,18
va	0,12	0,21	0,11	0,14
gha/va	0,08	0,06	0,00	-0,09
gha/va_varian	0,16	0,18	0,16	0,21
tta	0,21	0,19	0,20	0,29
da	0,36	0,29	0,35	0,36
ya	-0,08	0,07	0,15	0,11
a	0,47	0,18	-0,02	0,20
e	0,19	0,39	0,40	0,12
u	0,38	0,08	-0,03	0,02
Vert-bar att	-0,04	0,05	0,10	0,04
Vert-bar no-at	0,32	0,08	0,10	0,21
short bar	-0,03	0,05	0,10	-0,07
central	0,13	0,19	0,38	0,15
without	0,01	0,12	0,31	0,37
lower ra	0,26	-0,09	0,05	0,01
empty square	-0,04	-0,08	0,00	0,14
end in loop	0,04	0,11	-0,02	0,07
three	-0,09	0,10	0,10	0,02
Three-variant	0,00	-0,01	0,07	0,14
two_variant	0,13	0,04	-0,01	0,06
Ya-arc	0,22	0,16	-0,08	0,21
horiz. Att.	0,16	0,08	0,01	0,11
na/ta	-0,01	0,11	0,02	0,08