

Simplified Chinese Character Distance Based on Ideographic Description Sequences

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Abstract

Character encoding systems have long overlooked the internal structure of characters. Ideographic Description Sequences, which explicitly represent spatial relations between character components, are a potential solution to this problem. In this paper, we illustrate the utility of Ideographic Description Sequences in computing edit distance and finding orthographic neighbors for Simplified Chinese characters. In addition, we explore the possibility of using Ideographic Description Sequences to encode spatial relations between components in other scripts.

Keywords: Ideographic Description Sequences, Character distance, Character Neighbors

1. Introduction

Storage and communication of written text using digital computers requires conventions for encoding characters. Early efforts at establishing encoding standards were driven by practicality and economy of space. Developed in 1963, the American Standard Code for Information Interchange (ASCII; [American National Standards Institute, 1995](#)) lies at the basis of most character encoding systems in use today. ASCII uses a 7-bit encoding, with 32 of the 128 positions allocated to communication control characters and the other 96 reserved for numbers, upper- and lowercase letters of the English alphabet, and punctuation. As computer technology spread, ASCII was succeeded by ISO-8859 ([ISO/IEC, 1987](#)) which, with 8-bit encoding and language specific versions, enabled the encoding of characters for a wider variety of alphabetic writing systems (e.g., ISO 8859-5 for Cyrillic, ISO-8859-11 for Thai). Accommodation for storing the many characters used in CJK (Chinese, Japanese, Korean) writing systems, came with the Unicode Standard, with different variants allowing for up-to 32-bit encoding (>4 billion characters).

The legacy of ASCII lead to these successive standards allocating more and more space for individual characters instead of incorporating *compositionality*, which is a design feature of most writing systems (English writing being a notable exception). For instance, for writers of French it is understood that most vowels can be accented, yet ISO-8859-1 has different slots for â, ê, î, ô, and û; á, é, í, ó, and ú; etc. For other writing systems, such as Chinese, compositionality is the norm, rather than the exception.

Recognizing that it was necessary to represent characters that do not have a dedicated slot, such as rare or novel Chinese characters, Unicode 15.1 ([Unicode Consortium, 2023](#)) introduced Ideo-



Figure 1: Chinese character *biang1* 'the sound of slapping and kneading noodles during noodle-making'. The ideographic description sequence for this character is 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔 𠂔. 長馬長 𠂔心.

graphic Description Sequences (IDSs) as a principled approach to encoding characters compositionally.¹ Figure 1 shows the rendition of a rare character using an IDS.

Because of their ability to encode and represent characters compositionally, IDSs have a wide range of applications. In this paper, we will focus on a novel application, namely the use of IDSs to compute distance between Chinese characters. As section 2 will show, psycholinguistic literature has demonstrated that the identification of written words is influenced by their orthographic neighbors. Determining the orthographic neighbors of a word requires the ability to compute distances between any pairs of words. This is relatively straightforward to do in a language such as English, because most words do not have a hierarchical structure and characters are not compositional. It is far more difficult to do for Chinese characters.

Section 2 introduces related work on how diacritics and spatial relations influence word processing in various writing systems, providing theoretical background to support their explicit representations. Section 3 demonstrates a practical appli-

¹Although the term *ideographic* is widespread, it is inaccurate. Chinese writing, specifically, is considered morphosyllabic ([DeFrancis, 1989](#); [Gorman and Sproat, 2023](#)).

ciples (Köhler, 1967; Todorovic, 2008) and feature integration theory (Treisman and Gelade, 1980).

3. Character Distance in Simplified Chinese Script

Ideographic description sequences were created to encode the spatial arrangement of components for CJK Unified Ideographs.² Unicode 15.1 (Unicode Consortium, 2023) defines eighteen ideographic description characters (IDCs), twelve of which are commonly used (Table 1).

An IDS consists of an IDC followed by its arguments, which can be either ideographs or another IDC. For instance, the IDS for the character 英 *ying* 'blossom' is 央⁺⁺, where 央 signifies top-down arrangement of the arguments ⁺⁺ and 央. Because the number of arguments to an IDC is always known, IDSs allow for nesting and concatenation. The ability to nest IDCs makes it possible to render complex spatial arrangements. For instance, the IDS for the character 𪛗 *xiao* 'a mythic beast' is 𪛗¹ 𪛗² 𪛗³ 𪛗⁴ 𪛗⁵ 𪛗⁶ 𪛗⁷ 𪛗⁸ 𪛗⁹ 𪛗¹⁰ 𪛗¹¹ 𪛗¹² 𪛗¹³ 𪛗¹⁴ 𪛗¹⁵ 𪛗¹⁶ 𪛗¹⁷ 𪛗¹⁸ 𪛗¹⁹ 𪛗²⁰ 𪛗²¹ 𪛗²² 𪛗²³ 𪛗²⁴ 𪛗²⁵ 𪛗²⁶ 𪛗²⁷ 𪛗²⁸ 𪛗²⁹ 𪛗³⁰ 𪛗³¹ 𪛗³² 𪛗³³ 𪛗³⁴ 𪛗³⁵ 𪛗³⁶ 𪛗³⁷ 𪛗³⁸ 𪛗³⁹ 𪛗⁴⁰ 𪛗⁴¹ 𪛗⁴² 𪛗⁴³ 𪛗⁴⁴ 𪛗⁴⁵ 𪛗⁴⁶ 𪛗⁴⁷ 𪛗⁴⁸ 𪛗⁴⁹ 𪛗⁵⁰ 𪛗⁵¹ 𪛗⁵² 𪛗⁵³ 𪛗⁵⁴ 𪛗⁵⁵ 𪛗⁵⁶ 𪛗⁵⁷ 𪛗⁵⁸ 𪛗⁵⁹ 𪛗⁶⁰ 𪛗⁶¹ 𪛗⁶² 𪛗⁶³ 𪛗⁶⁴ 𪛗⁶⁵ 𪛗⁶⁶ 𪛗⁶⁷ 𪛗⁶⁸ 𪛗⁶⁹ 𪛗⁷⁰ 𪛗⁷¹ 𪛗⁷² 𪛗⁷³ 𪛗⁷⁴ 𪛗⁷⁵ 𪛗⁷⁶ 𪛗⁷⁷ 𪛗⁷⁸ 𪛗⁷⁹ 𪛗⁸⁰ 𪛗⁸¹ 𪛗⁸² 𪛗⁸³ 𪛗⁸⁴ 𪛗⁸⁵ 𪛗⁸⁶ 𪛗⁸⁷ 𪛗⁸⁸ 𪛗⁸⁹ 𪛗⁹⁰ 𪛗⁹¹ 𪛗⁹² 𪛗⁹³ 𪛗⁹⁴ 𪛗⁹⁵ 𪛗⁹⁶ 𪛗⁹⁷ 𪛗⁹⁸ 𪛗⁹⁹ 𪛗¹⁰⁰ 𪛗¹⁰¹ 𪛗¹⁰² 𪛗¹⁰³ 𪛗¹⁰⁴ 𪛗¹⁰⁵ 𪛗¹⁰⁶ 𪛗¹⁰⁷ 𪛗¹⁰⁸ 𪛗¹⁰⁹ 𪛗¹¹⁰ 𪛗¹¹¹ 𪛗¹¹² 𪛗¹¹³ 𪛗¹¹⁴ 𪛗¹¹⁵ 𪛗¹¹⁶ 𪛗¹¹⁷ 𪛗¹¹⁸ 𪛗¹¹⁹ 𪛗¹²⁰ 𪛗¹²¹ 𪛗¹²² 𪛗¹²³ 𪛗¹²⁴ 𪛗¹²⁵ 𪛗¹²⁶ 𪛗¹²⁷ 𪛗¹²⁸ 𪛗¹²⁹ 𪛗¹³⁰ 𪛗¹³¹ 𪛗¹³² 𪛗¹³³ 𪛗¹³⁴ 𪛗¹³⁵ 𪛗¹³⁶ 𪛗¹³⁷ 𪛗¹³⁸ 𪛗¹³⁹ 𪛗¹⁴⁰ 𪛗¹⁴¹ 𪛗¹⁴² 𪛗¹⁴³ 𪛗¹⁴⁴ 𪛗¹⁴⁵ 𪛗¹⁴⁶ 𪛗¹⁴⁷ 𪛗¹⁴⁸ 𪛗¹⁴⁹ 𪛗¹⁵⁰ 𪛗¹⁵¹ 𪛗¹⁵² 𪛗¹⁵³ 𪛗¹⁵⁴ 𪛗¹⁵⁵ 𪛗¹⁵⁶ 𪛗¹⁵⁷ 𪛗¹⁵⁸ 𪛗¹⁵⁹ 𪛗¹⁶⁰ 𪛗¹⁶¹ 𪛗¹⁶² 𪛗¹⁶³ 𪛗¹⁶⁴ 𪛗¹⁶⁵ 𪛗¹⁶⁶ 𪛗¹⁶⁷ 𪛗¹⁶⁸ 𪛗¹⁶⁹ 𪛗¹⁷⁰ 𪛗¹⁷¹ 𪛗¹⁷² 𪛗¹⁷³ 𪛗¹⁷⁴ 𪛗¹⁷⁵ 𪛗¹⁷⁶ 𪛗¹⁷⁷ 𪛗¹⁷⁸ 𪛗¹⁷⁹ 𪛗¹⁸⁰ 𪛗¹⁸¹ 𪛗¹⁸² 𪛗¹⁸³ 𪛗¹⁸⁴ 𪛗¹⁸⁵ 𪛗¹⁸⁶ 𪛗¹⁸⁷ 𪛗¹⁸⁸ 𪛗¹⁸⁹ 𪛗¹⁹⁰ 𪛗¹⁹¹ 𪛗¹⁹² 𪛗¹⁹³ 𪛗¹⁹⁴ 𪛗¹⁹⁵ 𪛗¹⁹⁶ 𪛗¹⁹⁷ 𪛗¹⁹⁸ 𪛗¹⁹⁹ 𪛗²⁰⁰ 𪛗²⁰¹ 𪛗²⁰² 𪛗²⁰³ 𪛗²⁰⁴ 𪛗²⁰⁵ 𪛗²⁰⁶ 𪛗²⁰⁷ 𪛗²⁰⁸ 𪛗²⁰⁹ 𪛗²¹⁰ 𪛗²¹¹ 𪛗²¹² 𪛗²¹³ 𪛗²¹⁴ 𪛗²¹⁵ 𪛗²¹⁶ 𪛗²¹⁷ 𪛗²¹⁸ 𪛗²¹⁹ 𪛗²²⁰ 𪛗²²¹ 𪛗²²² 𪛗²²³ 𪛗²²⁴ 𪛗²²⁵ 𪛗²²⁶ 𪛗²²⁷ 𪛗²²⁸ 𪛗²²⁹ 𪛗²³⁰ 𪛗²³¹ 𪛗²³² 𪛗²³³ 𪛗²³⁴ 𪛗²³⁵ 𪛗²³⁶ 𪛗²³⁷ 𪛗²³⁸ 𪛗²³⁹ 𪛗²⁴⁰ 𪛗²⁴¹ 𪛗²⁴² 𪛗²⁴³ 𪛗²⁴⁴ 𪛗²⁴⁵ 𪛗²⁴⁶ 𪛗²⁴⁷ 𪛗²⁴⁸ 𪛗²⁴⁹ 𪛗²⁵⁰ 𪛗²⁵¹ 𪛗²⁵² 𪛗²⁵³ 𪛗²⁵⁴ 𪛗²⁵⁵ 𪛗²⁵⁶ 𪛗²⁵⁷ 𪛗²⁵⁸ 𪛗²⁵⁹ 𪛗²⁶⁰ 𪛗²⁶¹ 𪛗²⁶² 𪛗²⁶³ 𪛗²⁶⁴ 𪛗²⁶⁵ 𪛗²⁶⁶ 𪛗²⁶⁷ 𪛗²⁶⁸ 𪛗²⁶⁹ 𪛗²⁷⁰ 𪛗²⁷¹ 𪛗²⁷² 𪛗²⁷³ 𪛗²⁷⁴ 𪛗²⁷⁵ 𪛗²⁷⁶ 𪛗²⁷⁷ 𪛗²⁷⁸ 𪛗²⁷⁹ 𪛗²⁸⁰ 𪛗²⁸¹ 𪛗²⁸² 𪛗²⁸³ 𪛗²⁸⁴ 𪛗²⁸⁵ 𪛗²⁸⁶ 𪛗²⁸⁷ 𪛗²⁸⁸ 𪛗²⁸⁹ 𪛗²⁹⁰ 𪛗<

When considering *distance* between the simplified Chinese characters 芍 *shao2* 'peony', 顶 *ding3* 'roof', and 英 *ying1* 'blossom', one approach would be to say that they are all different characters. Another approach could consist of noting that 芍 and 英 are both vertically arranged and have the element 艹 in common, whereas 顶 has no similarities to the other two characters, either in layout or components.

Existing methods for character similarity for Chinese characters can be divided in two main types: stroke-based and, more commonly, component-based. An abundance of literature defines the degree of character similarity based on shared component(s). In single-component comparison (Leck et al., 1995; Chen and Juola, 1982; Yeh and Li, 2002; Perfetti and Zhang, 1991), radicals (e.g., 蕉 *jiao1* 'banana' & 荐 *jian4* 'to recommend') or phonetic components (e.g., 煤 *mei2* 'coal' & 谋 *mou2* 'to plan') are used. Less often, smaller stroke patterns (e.g., 兑 *dui4* 'to exchange' & 分 *fen1* 'to divide'; Liu and Lin, 2008) and structural information (e.g., 啄 *zhuo2* 'to peck' & 佻 *ruo4* 'such'; Yeh et al., 1997) are used. Most of these methods define similarity in a binary way: a pair of characters is either similar or it is not. In the following sections, we propose an alternative method which is based on using edit distance on fully-decomposed IDSs and compare it to the existing approaches.

The Recognition by Components model (Biederman, 1987), asserted the significance of structural representations in object recognition. According to the model, the visual system recognizes an object by analyzing spatial arrangements of basic geometric shapes, such as cubes and cones. Transferring this to the domain of character recognition (Grainger et al., 2008), the relative positioning of components in a character is an important indicator of visual characteristics, helping to distinguish between characters (Lu et al., 2002). For example, the Chinese character 音 *yin1* 'sound' is distinguishable from another 昱 *yu4* 'bright' only by the relative positioning of components. The same is true for the diacritic letters š and ȝ in the orthography of Yoruba in Nigeria. Arguably, even letters of Ъ and Ь in Cyrillic script are compositionally similar, with a more nuanced difference in line orientation.

²CJK Unified Ideographs refers to a shared set of characters used in the writing systems of Chinese, Japanese, and Korean languages, all of which incorporate Han characters and their variations. CJKV extends the scope to include Vietnamese, which historically used Han characters.

IDC	Unicode	Name	Example	Example IDS
☐	U+2FF0	Ideographic Description Character Left to Right	作	☐彳 作
☐	U+2FF1	Ideographic Description Character Above to Below	思	☐田心
☐	U+2FF2	Ideographic Description Character Left to Middle and Right	街	☐彳圭于
☐	U+2FF3	Ideographic Description Character Above to Middle and Below	帛	☐ヨ巾
☐	U+2FF4	Ideographic Description Character Full Surround	回	☐☐☐
☐	U+2FF5	Ideographic Description Character Surround from Above	网	☐囗☐义义
☐	U+2FF6	Ideographic Description Character Surround from Below	凶	☐囗义
☐	U+2FF7	Ideographic Description Character Surround from Left	区	☐ㄣ义
☐	U+2FF8	Ideographic Description Character Surround from Upper Left	庆	☐广大
☐	U+2FF9	Ideographic Description Character Surround from Upper Right	句	☐ㄣ口
☐	U+2FFA	Ideographic Description Character Surround from Lower Left	这	☐辶文
☐	U+2FFB	Ideographic Description Character Overlaid	巫	☐工从

Table 1: The table provides IDCs, their Unicode, names, example characters, and Ideographic description sequences for the character.

3.1. Character distance using fully decomposed IDSs

We retrieved a dataset with IDSs for Chinese characters from an online repository³, which in turn was derived from the Character Information Service Environment (CHISE) IDS database⁴ (Morioka and Wittern, 2002). Part of the open-source CHISE project to expand general-purpose coded character sets, the IDS database contains most of the CJKV Unified Ideographs of ISO/IEC 10646 (Morioka, 2015).

To limit the list to Chinese characters used in mainland China, we selected only the 20,830 characters documented in Xinhua Dictionary (<http://xh.5156edu.com>). Then, we normalized the selected IDSs by recursively replacing components that could be further decomposed by their corresponding IDS. The result was a set of fully decomposed IDSs. Inspection of the resulting IDSs showed that, in addition to the 12 IDCs, only 545 basic characters were required to encode the over 20,000 selected characters.

Levenshtein distance (LD) is defined as the number of insertions, deletions, and substitutions operated on a string to turn it into another string (Levenshtein, 1966). Inspired by Kruskal (1983), we gave the substitution a cost of 2 and the other two operations a cost of 1 (see Figure 2).

3.1.1. IDS distance vs methods based on shared components

Some Chinese characters incorporate the same radicals and residuals: 案 *an4* 'instance' & 桉 *an1* 'the eucalyptus tree', 召 *zhao4* 'to summon' & 叨 *dao1* 'to chatter', and 峯 *feng1* 'peak' & 峰 *feng1* 'summit'. When similarity is based on shared components as in the examples (i.e., 吃 *chi1* 'to eat',

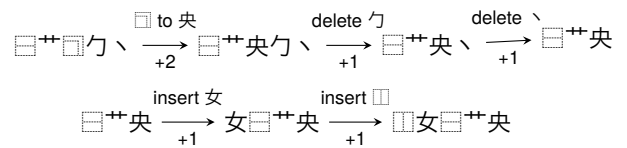


Figure 2: The first example illustrates substitution and deletion. Converting 芍 *shao2* 'peony' (IDS: ☐彳☐ㄣ) to 英 *ying1* 'blossom' (IDS: ☐彳☐央) involves one substitution and two deletions, resulting in an edit distance of 4. The second example illustrates insertion: Transforming 英 to 嫵 *ying1* beauty (IDS: ☐女☐彳☐央) requires the insertion of ☐女 and ☐彳, resulting in an edit distance of 2.

员 *yuan2* 'member', 哲 *zhe2* 'philosophical', and 加 *jia1* 'to add') provided in the work of Yeh and Li (2002), these pairs are identical because they all have the same components. This method falls short with respect to structural differences.

Figure 3 shows the IDS distance for the same characters. The IDS distance between 案 and 桉 is 4, equal to that between 召 & 叨, whereas closer are 峯 & 峰, which are only different in layout and have a distance of 2.

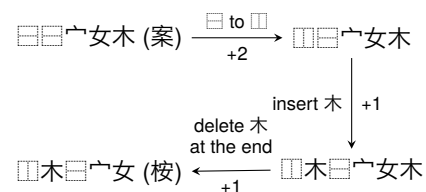


Figure 3: The edit distance of 案 & 桉 is 4, summing up 1 substitution, 1 insertion and 1 deletion.

³<https://github.com/cjkvi/cjkvi-ids>

⁴<https://gitlab.chise.org/CHISE/ids>

3.1.2. IDS distance vs methods based on radical-level shared components and character structures

The spatial arrangements of components in Chinese characters are highly correlated with their functions (semantic or phonetic). In various applications, characters that have identical structure and shared components are considered similar and selected as stimuli (Leck et al., 1995; Chen and Juola, 1982). Hence, these methods do not identify similarity among characters sharing both structure and components, but not the function of components. For instance, 杏 *xing4* 'apricot' and 呆 *dai1* 'dull' have different component order and semantic radical, but are otherwise identical. Figure 4 shows how, in comparison, IDS-based distance addresses this.

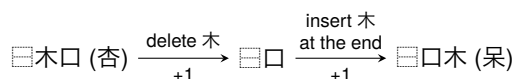


Figure 4: The edit distance of 杏 & 呆 is 2 via one deletion and one insertion.

3.1.3. IDS distance vs methods based on sub-radical shared components and character structures

Liu and Lin (2008) go beyond the radical - residual level and explore smaller stroke patterns in computing similarity between Chinese characters. They decompose a character into a set of 24 basic elements defined in the Cangjie code by Chu (1979). A character is represented by its structure (one of nine layout patterns, encoded as a real value) followed by up to three components. For example, 相 *xiang4* 'appearance' has a representation of '2 (layout code) - 木 (part 1) - 月山 (part 2)'. Although this approach goes a long way toward addressing the compositionality of characters in a principled manner, the limited basic components do not allow for an unambiguous specification of characters. In other words, in many cases the decomposition does not allow for recombination of the original characters. Using only nine layout patterns is also insufficient, as Simplified Chinese characters can be as complex as encompassing up to 32 strokes (e.g., 龕 *da2* 'depicting the majestic soaring of a dragon'). Instead, using IDS, we encode character structures by explaining structural information between just two or three components predetermined by IDCs. This granularity is also a reason why our method produce faithful results.

The IDS representation does not have structural ambiguity between sequences. In the few cases where we have found characters to share the same IDS representation (56 out 20,830), this

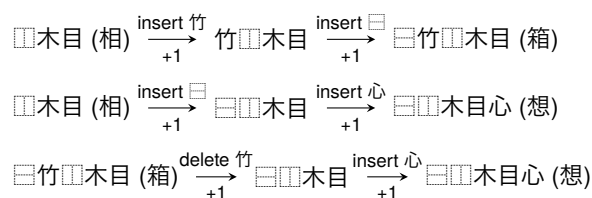


Figure 5: The figure shows the process to get edit distance among characters 相, 箱, and 想. We turn 相 into 箱 via two insertions, as is the case for 相 & 想. Converting 箱 to 想 requires one deletion and one insertion.

concerned historical variants of the same character with slightly different stroke variants. Figure 5 shows the IDS distance between 相 *xiang4* 'appearance', 箱 *xiang1* 'case', and 想 *xiang3* 'to miss', which according to Liu and Lin (2008) would be dissimilar. It may seem to be surprising that the IDS distance between 箱 and 想 is so small, but, in addition to overlapping components, these two are both vertical characters hierarchically enclosing a horizontal character.

3.1.4. Three basic elements to compute character similarity

It seems that, from the above-mentioned examples, it is next to impossible to evaluate the degree of character similarity without the integration of three basic elements:

- components (stroke patterns or smaller), as opposed to single-component comparison.
- layouts governing components, in comparison with character structure possibly as a result of single component comparison.
- relative positions of components.

We suggest that if we want to claim that characters are similar, we need to make these three elements explicit.

One of the limitations of using IDS to compute edit distance is its comprised ability to differentiate relative positions of components in some cases. For example, characters 呆 *dai1* 'dull', 宋 *song4* 'a surname', and 告 *gao4* 'to sue' have the same edit distance of 2, but while we rule in component position, 告 should be further away from 呆, as their shared component is located differently. In order to differentiate the effect of component order, one possible method is to increase the weight of insertion. However, this would lead to an asymmetry of pairwise distances, which requires further modification.

香		鬱	
Neighbors	Distance	Neighbors	Distance
香	0	鬱	0
查	2	鬱	6
查	2	鬱	10
杏	2	邕	12
李	2	彬	18
李	2	俊	19
沓	2	糴	20
木	2	鏤	20
杰	2	菌	20
泰	2	滷	20
崑	2	焚	20
呆	2	楠	20
杲	2	樊	20
旻	2	璠	20
柰	2	鹵	20
早	2	乘	21
見	2	兇	21
日	2	官	21
旦	2	爻	21
	2	吉	21

Table 2: Neighbors and their pairwise distance to 杳 (orthographically simple and dense) and to 鬱 (orthographically complex and distinct).

3.2. Character Neighbors

By computing character distance, it is possible to cluster orthographically similar characters by exhausting pairwise distances among all characters and sorting the result. Table 2 provides twenty nearest neighbors for 杳 *yao3* 'dim' and 鬱 *yu4* 'lush and growing abundantly'.

[illegible]

To address this, we normalize distance as follows: Let N_i be the length of IDS of character C_i and N_j be the length of IDS of character C_j :

$$max\ distance = \min(N_i, N_j) \times 2 + |N_i - N_j|$$

where *max distance* represents the upper bound of the cost from possible operations. The distance metric can then be normalized by calculating the relationship between the cost of operations actually used and the maximum possible costs. The

normalized distance is calculated as:

$$normalized\ distance = \frac{edit\ distance}{max\ distance}$$

where *normalized distance* indicates a measure where lower values signify higher operational congruence and thus closer distance.

Twenty closest neighbors for 鬱 based on normalized distance are given in Table 3. Note that the normalized distance of 鬱 and 鬱 is 0.545, smaller than that of 鬱 and 匕, though not shown in the table, at 0.793. We can see that the adjusted distance reveals a cluster of character pattern that is closer to human intuition.

4. IDS as a general approach to expressing component relations in any script

There are some advantages of the ideographic description sequences. First, they have the potential to be used to describe attested compositional characters in any script. For instance, French *café* could be represented as (c, a, f, ☐, ´, e), with the description character ☐ indicating that the two subsequent elements are to be arranged top-down. Second, they provide the possibility to form new compositional characters. Finally, when words are represented using concatenated ideographic description sequences, they allow for more accurate measurement of word similarity. For instance, in French, the word *pâte* can be considered to differ by one character from both *pate* and *pâté*, but in the same way it can also be considered to differ by the absence or presence of a diacritic on one of the characters.

In practice, the arguments to a particular IDC are quite predictable. For example, the IDC $\square$ almost always has a semantic radical as its left component and a phonetic residual as its right component. The spatial rendering thus typically also encodes a specific relationship. Taking this idea further, we can consider an IDC as a way of connecting a specific type of linguistic relationship to a specific spatial rendering (e.g., morphological, semantic, ontological). For instance, Table 4 shows how one could consider the components of compound words as arguments to a relationship operator which horizontally concatenates the components. This would allow distinguishing compounds from non-compounds, at least in the underlying sequence. But instead of horizontal arrangement, we could also replace the horizontal IDC with an equivalent vertical IDC to achieve a different kind of representation. In some applications, English text could then be rendered as in Figure 6. On top of this, there are also a wide range of other possible applications for IDS: creating novel

Neighbors	鬱	鬱	鬱	鬱	鬱	鬱	鬱	鬱	鬱	鬱
Normalized Distance	0	0.125	0.192	0.3	0.442	0.463	0.463	0.5	0.5	0.5
Neighbors	壩	壩	壩	壩	壩	壩	壩	壩	壩	壩
Normalized Distance	0.5	0.524	0.524	0.526	0.526	0.526	0.526	0.529	0.545	0.545

Table 3: Twenty neighbors to 鬱 based on normalized distance. Note that after adjusting for the complexity level of the characters, the result is closer to human intuition.

Compound word	IDS horizontal	IDS vertical	Representation vertical
red dwarf	red, , dwarf	red, dwarf	red dwarf
red-blooded	red, -, blooded	red, blooded	red blooded
redhead	red, head	red, head	red head

Table 4: Table shows three compound words, IDS for their original forms, IDS for vertical placements, and resulting vertical renditions.

- Red dwarfs are the most common type of star in the Milky Way.
- He says he's a red blooded American male!
- Unusually for a red head, she tans easily.

Figure 6: A demonstration of rendering compound words in vertical layouts. Example sentences were retrieved from online Cambridge Dictionary (<https://dictionary.cambridge.org>).

sequences; creating or adapting representations for under-resourced languages; rendering linguistic relationships spatially; substituting layouts, etc.

Examples of character IDS application in different scripts are shown in Table 5. While we use existing IDCs designed for Simplified Chinese characters in these examples, specific IDCs may need to be created to allow for script characteristics.

5. Conclusion

In this paper, we demonstrated that IDSs can be used to more precisely calculate edit distance and orthographic neighbors for Simplified Chinese characters. In addition, we explored the possibility of using IDSs to typographically represent morphological relationships. While Unicode currently only uses IDSs for CJK writing systems, the ability to represent characters compositionally gives IDSs a wide range of application beyond these scripts. In this way, representing characters and words using IDSs can offer methodological improvements in several areas.

Character	Script / Language	IDS
Ա	Adlam	Ա, Յ, Ա
Ъ	Cyrillic	Ъ, Ъ, Ъ
님	Korean	님, 님, 님, 님, 님
Ϸ	Greek	Ϸ, Ϸ, Ϸ
Ł	Latin	Ł, Ł, Ł
Đ	Latin	Đ, Đ, Đ
Ł	Latin	Ł, Ł, Ł, -, -
Æ	Latin / Cyrillic	Æ, A, E
Æ	Latin	Æ, -, Æ, A, E
Ä	Latin	Ä, -, Ä, A
ஊ	Tamil	ஊ, ஊ, ஊ

Table 5: Example characters represented as IDS in several scripts like Adlam, Cyrillic, Korean, Greek, Latin, and Tamil.

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