A CLASSIFICATION METHOD FOR JAPANESE SIGNS USING MANUAL MOTION DESCRIPTIONS

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SUMMARY In this paper, we propose a classification method for signs in *Japanese Sign Language* (JSL). The method is based on the similarity between *manual motion descriptions* (MMDs) of signs. MMDs are the verbal descriptions of signs. The measure of similarity between MMDs is derived from their *longest common subsequence* (LCS) of MMDs. By computing feature vectors of n properties from a finite set of MMDs and plotting them in the n-dimensional Euclidean space, the similarity between signs can be regarded as an internal angle between the vectors. The result of our experiment is that the significant sign families can be obtained.

1. INTRODUCTION

Stokoe (1960) is the first linguist to deal with the structure of signs in the same way as that of oral words. He noted that there were three kinds of parameters in describing the sign in *American Sign Language* (ASL) as follows: (1) the location of the signs relative to the body, (2) the hand-shape of hands involved in articulating the sign and, (3) the movement of hands. Other linguists (Friedman 1977, Battison 1978) have claimed that a fourth parameter is obligatory, that is, the spatial orientation of the hands relative to the body. In *Japanese Sign Language* (JSL), a few linguists (Tanokami 1979, Kanda 1982) took the similar approaches.

Thus, we need to specify the *location*, *hand-shape*, *movement* and *orientation* of the hands to describe the sign. Furthermore, it is interesting to note that a change in only one of the significant elements in hand-shape, location, orientation and movement often results in changing the meaning (ex., antonym, synonym). The notation systems proposed by linguists can provide a very detailed and broader representation to describe signs. It is, however, not easy to transform the sign into the notation. For this reason, it is too cost to collect a large amount of sign data.

Consider, for example, a minimal pair in the movement as shown in Fig.1.

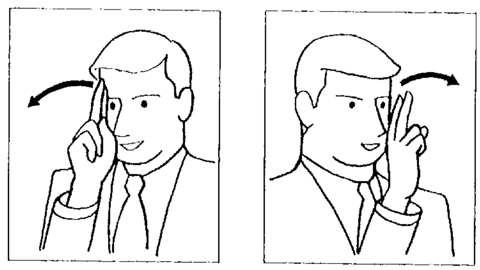


Fig 1: The Minimal Pair of Signs (午前 (a.m.), 午後 (p.m.))

It is clear that the minimal pair { 午前 (*a.m.*), 午後 (*p.m.*)} means the antonym semantically and represents the symmetry visually. Typical sign dictionary consists of illustrations or photographs and the verbal descriptions, we called the descriptions *manual motion descriptions* (MMDs) represented as text written in natural language.

It can be considered that a MMD represents information extracted from a series of the manual motions of the sign. It is not difficult to find the symmetry of signs by the contrast between two MMDs. For example, the contrast of words 右 (right) and 左 (left) can be obtained from comparing MMDs of 午後 (a.m.) with 午後 (p.m.) as follows.

右手の人差指と中指を立てて額の中央にあてて、{ 右に倒す 午前 / 左に倒す 午後 }

We describe a classification method for signs using mathematical techniques based on the similarity between MMDs.

2. DATA STRUCTURES FOR MMDS

This section describes the remarkable characteristics of MMD and a transformation method derived from them. The method means that MMDs can be transformed into the n-dimensional feature vectors.

2.1 The Remarkable Characteristics of MMDs

MMDs mean a kind of the verbal descriptions of the sign, which are written in Japanese language and has remarkable characteristics as follows:

- MMDs have more constraints on syntactic patterns and words than general Japanese sentences. In other words, there are some kind of syntactic patterns in MMDs.
- In Japanese, synonyms are often marked with the common *kanji*-characters. For example, each set of words $A = \{$ 右手, 左手, 両手 $\}$, $B = \{$ 親指, 人差指, 中指, 薬指, 小指 $\}$ has a common postfix *kanji*-character 手 or 指 and some kinds of semantic groups are constructed by them such as

$$\text{手}\,(\textit{hand}) \Rightarrow \begin{cases} \text{右・手}\,(\textit{right hand}) \\ \text{両・手}\,(\textit{left hand}) \\ \text{左・手}\,(\textit{both hands}) \end{cases}$$

$$\text{指}\,(\textit{finger}) \Rightarrow \begin{cases} \text{親・指}\,(\textit{thumb}) \\ \text{人差・指}\,(\textit{index finger}) \\ \text{中・指}\,(\textit{middle finger}) \\ \text{薬・指}\,(\textit{third finger}) \\ \text{小・指}\,(\textit{little finger}) \end{cases}$$

Thus, the combination of *kanji*-characters means semantic concatenation. Sato (1992) has also pointed out them in his paper.

2.2 Transformation into Feature Vectors

To represent the distribution of words mathematically, it is convenient to considered as points in the n-dimensional Euclidean space. The coordinates of points can be given as the n-dimensional feature vectors. Then, an internal angle between the vectors can be considered as the similarity between the words. In this case, properties of the feature vectors need to many points of view. (i.e., word frequency, part of speech, co-occurrence relation, and so on). In pattern recognitions, the same approaches have made use of recognizing pictures and letters. Therefore, we also select this approach which is signs are plotted in the n-dimensional Euclidean space. Feature vectors can be obtained by constructing a finite state automaton accepting MMDs as follows.

It is well known that finite state automata recognize finite state languages (see Aho,A.V., et al. 1974). If a class of patterns can be described in a finite state language, a finite state automaton can be constructed to recognize MMDs described this class of patterns.

Example.2.1

Let A=右手の親指を上げる, B=左手の親指を下げる and C=両手の小指を曲げる be MMDs. The finite state transition diagram of a automaton accepting the set of MMD is shown in Fig. 2.2.

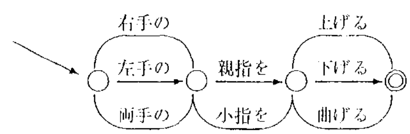


Fig 2: A Finite State Transition Diagram

Then, a regular expression derived from the above diagram is shown the following.

(右, 左, 両) 手の (親, 小) 指を (上, 下, 曲) げる.

Each *kanji- or kana-* character of the above regular expression can be considered as properties on the feature vectors for the sign. The feature vectors for the sign derived from MMDs are shown in Table 1.

	右	左	両	手	の	親	小	指	を	上	下	曲	げ	る
A	1	0	0	1	1	1	0	1	1	1	0	0	1	1
B	0	1	0	1	1	1	0	1	1	0	1	0	1	1
C	0	0	1	1	1	0	1	1	1	0	0	1	1	1

Table 1: The feature vectors derived from MMD

Thus, the signs can be represented as *14*-dimensional feature vectors, which can be defined as *bit vectors* $\in [0,1]$.

Furthermore, we can find a kind of syntactic pattern 〜の〜を〜, where 〜 means variables (noun,verb,...), and の (*no*) and を (*wo*) mean case markers.

3. SIMILARITY BETWEEN SIGNS

This section describes how a similarity between signs is computed. To compute similarity, we introduced *the longest-common-subsequence function* (LCS).

3.1 Similarity between MMDs

The result of the previous discussions can be summarized as follows:

1. Similarity between two signs can be considered as similarity between two MMDs.
2. When describing signs mathematically, it is convenient to regard them as points or feature vectors in the n-dimensional Euclidean space. The similarity measure between two signs is considered as an angle of two vectors.
3. If a finite state automata accepting MMDs can be constructed, properties of feature vectors can be placed all characters constructing MMDs.

Let $A = (a_1, a_2, ..., a_n)$ and $B = (b_1, b_2, ..., b_n)$ be n-dimensional feature vectors of signs. Then, the similarity measure between signs, denoted by $S(A, B)$, can be defined as follows:

DEF.1:The Similarity between Feature Vectors

$$S(A,B) = \cos^2\theta = \frac{(A,B)^2}{||A||^2||B||^2} \quad (1)$$

$$(0 \leq S(A,B) \leq 1)$$

where (A, B) is *the inner product* of vectors A and B, and can be computed as follows:

$$(A,B) = \sum_{k=1}^{n} a_k b_k$$

$||A||^2$ is *the squared Euclidean norm* of vector A and can be computed as follows:

$$||A||^2 = \left(\sqrt{(A,A)}\right)^2 = \left(\sqrt{\sum_{k=1}^{n} a_k^2}\right)^2 = \sum_{k=1}^{n} a_k^2$$

Namely, $||A||^2$ can be computed as the sum of $a_i = 1$ in vector A. (A, B) can be computed as the sum of $a_i \wedge b_i = 1$ in feature vectors A and B.

Recall the feature vectors of Table 1 in the last section. $||A||^2$ can be defined as a length of MMD related to vector A. In the same way, (A, B) can be defined as a length of a *longest common subsequence* of MMDs related to vectors A and B. We shall discuss it in detail.

3.2 Longest Common Subsequence

A subsequence of a given string is any string obtained by deleting zero or more symbols from the given string. A *longest common subsequence* (LCS) of two strings is a subsequence of both that is as long as any other common subsequence.

An LCS means that the number of matching characters considering the character order constraint. For example, if X = ***abcbdab*** and Y = ***bdcaba***, then an LCS of X and Y is ***bcba***, and has length 4 as shown in Fig. 3. The other LCS of X and Y are ***bdab*** and ***bcab***, and also have length 4.

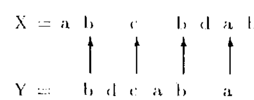


Fig 3: An LCS of X and Y

Let $A = a_1 a_2 ... a_m$ and $B = b_1 b_2 ... b_n$ be sequences. For a given sequence $X = x_1 x_2 ... x_l$, we define the ith prefix of X, for $i = 0, 1, ..., l$, as $X_i = x_1 x_2 ... x_i$. For example, if $X = abcde$, then $X_3 = abc$ and X_0 is the empty sequence. Then, an LCS of A and B, denoted by $LCS(A, B)$, can be computed efficiently as the following recursive formula using Dynamic Programming (for further details of LCS, see Thomas H, et. al. 1991).

$$LCS(A,B) = c(m,n) \quad (2)$$

$$c(i,j) = \begin{cases} c(i-1,j-1)+1 & \text{if } a_i = b_j, \\ \max\{c(i,j-1), c(i-1,j)\} & \text{if } a_i \neq b_j \end{cases}$$

where $c(i, j)$ is the length of an LCS of the sequences A_i and B_i. If $i = 0$ and/or $j = 0$, then $c(i, j) = 0$.

$c(i,j)$	b	d	c	a	b	a
a	0	0	0	1	1	1
b	1	1	1	1	2	2
c	1	1	2	2	2	2
b	1	1	2	2	3	3
d	1	2	2	2	3	3
a	1	2	2	3	3	4
b	1	2	2	3	4	4

Table 2: Table to Compute LCS of X and Y

The result of computing LCS is shown as follows.

Formally, let $A = a_1 a_2 ... a_m$ and $B = b_1 b_2 ... b_n$ be MMDs. Then, $S(A,B)$ mentioned previously can be defined as follows:

DEF.2: The similarity between MMDs

$$S(A,B) = \frac{LCS(A,B)^2}{mn} \tag{3}$$

$$(0 \leq S(A,B) \leq 1 = S(A,A))$$

Thus, we need not to construct a finite state automaton accepting a set of MMDs and to transform from MMDs to feature vectors. Therefore, the similarity computation based on the LCS is simpler and easier than the computation between the vectors.

Batagelj (1989) described that $S(A,B)$ have to satisfy the following two conditions.

1. $S(A,B) = S(B,A)$
2. $S(A,B) \leq S(A,A)$ or $S(A,B) \geq S(A,A)$

Obviously, the above similarity measure satisfies them.

3.3 An Experiment

We now show results of an experiment and verify the similarity measure between signs. We used data in *The Illustrated Sign Dictionary* (Maruyama 1984) for the following reasons. We made use the simple description data (1,527 entries), which were rendered machine readable data. By merging the same MMDs, in advance, 1,514 entries were obtained [1]. For example, 名前 (name) and バッジ (badge) in Table 3 means S(名前, バッジ) $= 1$.

[1] i.e., used pattern matching commands **awk** and **sed** on UNIX

The results of an experiment say that the similarities of 36 pairs are greater than 0.8 and 570 pairs are greater than 0.5.

similarity	sign.A	sign.B
0.97	失敗.D(failure)	落ちぶれる (drop)
0.97	以後 (after)	以外 (beside)
0.96	嬉しい (glad)	楽しい (happy)
0.93	働く (work)	仕事 (job)
0.91	女性 (woman)	男性 (man)
0.90	ワッペン (emblem)	名前 (name), バッヂ (badge)
0.88	娘 (daughtor)	息子 (son)
0.88	発達 (advancement)	向上 (improvement)
0.88	紹介 (introduce)	通訳 (interpreter)
0.87	比べる (compare)	バランス.B(balance)
0.86	証拠 (evidence)	証明 (proof)
0.84	悲しい (sad)	泣く (cry)
0.84	上がる (go up)	登る (climb)
0.83	裏 (back)	内 (inside)
0.83	迷う (hesitate)	動揺 (unrest)
0.83	下 (below)	上 (top)
0.83	横浜 (Yokohama)	滑らか (smooth)

Table 3: An Example for Minimal Pairs of Sins

Consider, for example, parts of the approximate similar pairs as shown in Table 3. A pair {娘 (*daughter*), 息子 (*son*)} means the antonym and the other pair {悲しい (*sad*), 泣く (*cry*)} means the synonym. Thus, these results means that the members of a similar pair have the common semantic component. In other words, by computing the similarity of MMD, minimal pairs of signs can be obtained.

The similarity of manual motions results in the similarity of meaning, which is a kind of sign formative units. That is, a minimal pair 娘 and 息子 have a common semantic component `children of parents` such as a motion `a hand is moved the forward related to the body` , and an individual semantic component `the female or male sex` such as using a little or thumb finger.

There are, however, a few exceptions in the above rule. For example, each of a pair {横浜 (*Yokohama*), 滑らか (*smooth*)} have different meaning, but both of them are derived from the same iconic motion of the object "razors". From the language pragmatics points of view, the important thing is that a meaning of signs changes in various context just as a meaning of a word "spring" changes in various context,

The point we wish to emphasize is that computing the similarity between MMDs results the significant minimal pair of sign.

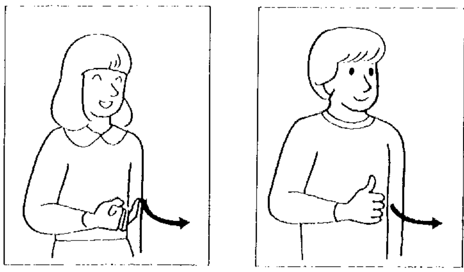


Fig 4: Signs of 娘 (daughter) and 息子 (son)

4. A CLASSIFICATION METHOD

4.1 Mathematical Notion

For a finite set X, a binary relation $R(X, X)$ that is *reflexive, symmetric and transitive* is called an *equivalence relation*. For each element x in X, we define a set A_x, which contains all the elements of X that are related to x by the equivalence relation. Formally,

$$A_x = \{y | (x, y) \in R(X, X)\}.$$

A_x is clearly a subset of X. The element x is itself contained in A_x due to the reflexivity of R; because R is transitive and symmetric, each member of A_x is related to all the other members of A_x. This set A_x is referred to as an **equivalence class** of $R(X, X)$ with respect to x. The family of all such equivalence classes defined by the relation, which is usually denoted by X/R, forms a partition on X.

4.2 A Classification Method

We describe how clustering a given finite set of signs using the similarity measure proposed in Section 3. The similarity relation $S(A, B)$ satisfies the following two conditions.

- reflexive: $S(A, A) = 1$
- symmetric: $S(A, B) = S(B, A)$

$S(A, B)$, however, doesn't satisfy the transitive condition. Then, we introduce the following inequality.

$$S(A, B) \geq \max\min\{S(A, C), S(C, B)\} \qquad (4)$$

Example 4.1

Let $X = \{a, b, c, d, e\}$ be a set of signs, and $X \times X = \{S(a, a), S(a, b), S(a, c), ..., S(e, e)\}$.
The similarity relation $S(X, X)$ can be represented as the following similarity matrix S.

S	a	b	c	d	e
a	1	0.2	0.5	0.3	0.8
b	0.2	1	0.3	0.5	0.3
c	0.5	0.3	1	0.2	0.7
d	0.3	0.5	0.2	1	0.2
e	0.8	0.3	0.7	0.2	1

$\Longrightarrow$

T	a	b	c	d	e
a	1	0.3	0.7	0.3	0.8
b	0.3	1	0.3	0.5	0.3
c	0.7	0.3	1	0.3	0.7
d	0.3	0.5	0.3	1	0.3
e	0.8	0.3	0.7	0.3	1

S can be transformed into the above transitive matrix T by a formula
$T(A, B) = \max\min\{S(A, C), S(C, B)\}$.

T	a	e	c	d	b
a	1	0.8	0.7	0.3	0.3
e	0.8	1	0.7	0.3	0.3
c	0.7	0.7	1	0.3	0.3
d	0.3	0.3	0.3	1	0.5
b	0.3	0.3	0.3	0.5	1

$\Longrightarrow$

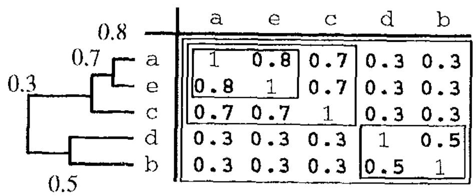
T	a	e	c	d	b
a	1	0.8	0.7		
e	0.8	1	0.7		
c	0.7	0.7	1		
d				1	0.5
b				0.5	1

T can be transformed into the other matrix by a matrix sorting operation which rearrange the attributes according to their correlation coefficients.

Thus, a set of the sign can be classified using the partition induced by the equivalence relation T_α with the appropriate threshold α ($1 \geq \alpha \geq 0$).

$X/T_{1.0} = \{ a, b, c, d, e \}$,
$X/T_{0.8} = \{ [a, e], c, d, b \}$,
$X/T_{0.7} = \{ [a, e, c], d, b \}$,
$X/T_{0.5} = \{ [a, e, c], [d, b] \}$,
$X/T_{0.0} = X/T_{0.3} = \{ [a, e, c, d, b] \}$.

Consequently, for every monotonically decreasing finite sequences of thresholds ($1 \geq \alpha_1 \geq \alpha_2 \geq ... \geq \alpha_k \geq 0$), the k-level hierarchy clusters in the form of a **dendrogram** can be obtained as shown in Fig 5. However, to construct the dendrogram is not our present purpose. The reason is that the similarity measure $S(A, B)$ has a feature of the curve $\cos^2\theta$. That is, as the similarities are close the maximum ($S(A, B) = 1$), gains of noise factor (i.e., inflection) can be ignored. Therefore, The low-level clusters (≤ 0.5) are not necessary for our purpose. We want to find the significant sign families than to obtain hierarchy structures.



	a	e	c	d	b
a	1	0.8	0.7	0.3	0.3
e	0.8	1	0.7	0.3	0.3
c	0.7	0.7	1	0.3	0.3
d	0.3	0.3	0.3	1	0.5
b	0.3	0.3	0.3	0.5	1

Fig 5: The k-level hierarchy clusters: *dendrogram*

4.3 An Experiment

To make discussions simpler, we used the sample data of MMDs (129 entries) including two key-words (characters) of 口 (mouth) 71 entries and 唇 (lips) 58 entries; because, a word 唇 can be identified with a word 口 in Japanese language. We wanted to obtain the results from extracting sign families rather than to obtain the hierarchy structure or the form of a dendrogram. The purpose of classifications is to focus on the minimal pairs of signs.

By merging the identical data that means $S(A, B) = 1$, 129 entries are merged into 101 entries. The total amount of sign pairs satisfying $S(A, B) \geq 0.6$ are 25 pairs, and a 31×31 similarity matrix is obtained. Then, the similarity matrix is transformed into a transitive matrix, and the equivalence classes can be obtained as shown in Table 6.

We classified given signs (129 entries) into 11 clusters and found that the largest amount of sign family is 赤い (RED)-family as follows:

23 entries : 赤 (red), 苺 (strawberry), 遺伝 (heredity), 日曜日 (Sunday), 火事 (fire), 速達 (express), リンゴ (apple), 血液 (blood), and so on.

This sign family has an essential common MMD "右手の人差指を下唇にあてて右に引く" and motion in Fig.7, and has semantic component "red".

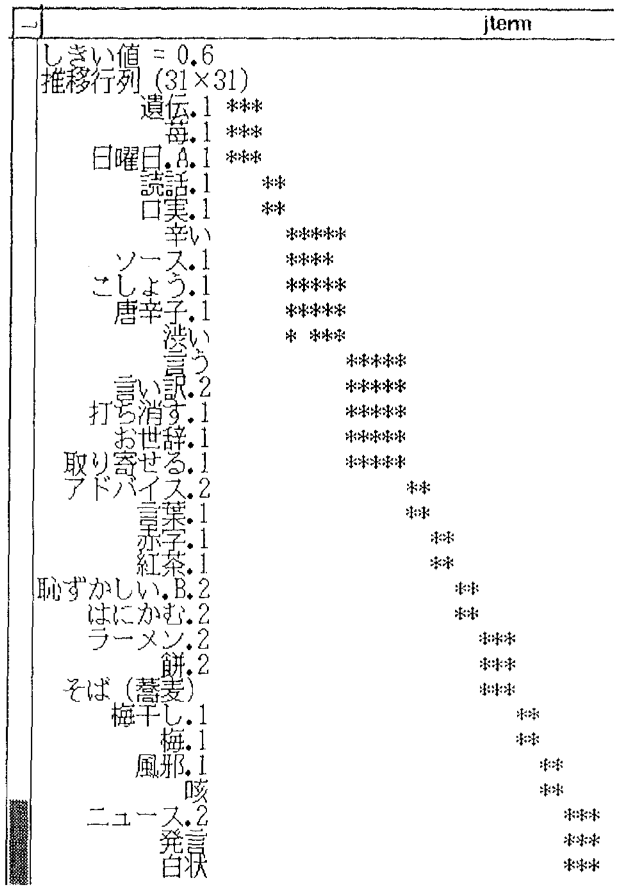


Fig 6: A Transitive Matrix

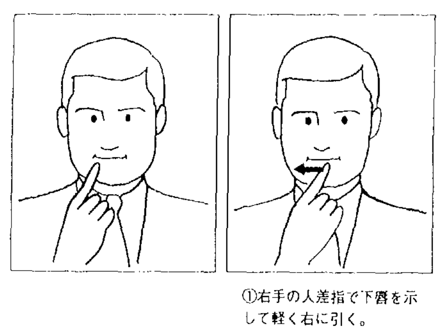
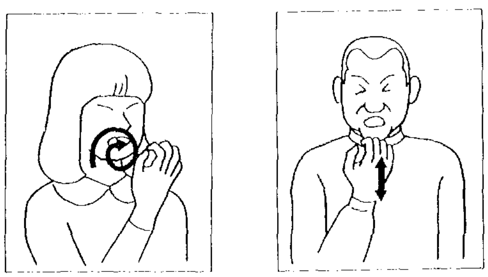


Fig 7: The MMD and Motion of 赤 (red)

That is, 遺伝 (heredity) derived from "blood", 日曜日 (Sunday) derived from the red numeric in the calendar, and 速達 (express) derived from the red-stamp on the letter, and so on.

Consider, for example, a family of signs { 辛い, ソース, こしょう, 唐辛子, 渋い } means $\{salty, Worcester-sauce, peper, red-paper, astringent\}$. The family has an essential common semantic component, which means "not sweet" represented as crooking all of fingers. The difference of a pair(辛い (salty), 渋い (astringent)) is whether to be rotated or up and down.



①五指を折り曲げた右手を口の前でまわす。

①五指を折り曲げた右手を口の前で二度ほど上下する。

Fig 8: Signs of 辛い (salty) and 渋い (astringent)

5. CONCLUDING REMARKS

We have proposed a new classification method for signs in JSL. The method is based on the similarity between the verbal descriptions of signs, called *Manual Motion Description* (MMD). The similarity of signs can be considered as an internal angle between feature vectors represented as points in the n-dimensional Euclidean space. By computing feature vectors of n properties from MMDs and plotting them in the n-dimensional Euclidean space, an angle between two vectors can be considered as the similarity between the two signs. As a classification method, we have introduced a finite set of signs divided into equivalence classes on the equivalence relation with the k level.

As further research directions, we will apply this similarity measure to the retrieval of the similar signs in *Sign Electronic Dictionary* (SED). When we look at an unknown sign, if the sign motion image can be represented using the form of MMDs, the best matched sign or the sign family can be retrieved by computing the similarity among a given MMD and MMDs of signs in SED.

ACKNOWLEDGMENTS

We would like to thank to Dr.Takeshi Kumagai for reading the manuscript and making a number of helpful suggestions. We special thanks are due to a publisher *KK-Dainamikku Seraze* for permission to reproduce illustrations in *Illustrated Sign Dictionary* [10].

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