

Using Strong's Numbers in the Bible to test an Automatic Alignment of Parallel texts

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We describe a method for the automatic alignment of parallel texts using co-occurrence statistics. The assumption of this approach is that words which are often found together are linked in some way. We employ this assumption to automatically suggest links between words in different languages, using Bible verses as information units. The result is a word-by-word alignment between different translations of the Bible. The accuracy of our method is evaluated by using the so-called Strong's Numbers as a benchmark. Overall, the performance is high, indicating that this approach can be used to give an approximate gloss of Bible verses.

1. Introduction

Using parallel texts for linguistic typology is a highly interesting and potentially fruitful approach. However, currently such work is tedious and highly laborious, as every example sentence from every language in the typological sample has to be interpreted individually by a researcher. In this paper, we will propose a method of automatic alignment between translations that could help the interpretation of sentences in a language not intimately known to a researcher, thus possibly speeding up the process of gathering typological data. We envision a system in which particular stretches of text from a language well known to a typological researcher are selected as potentially interesting. Then the system will return the translational equivalents of these sentences in another language, suggesting also an approximate gloss. Of course, the selection, full analysis, and interpretation of the sentences will still be left to the typologist. As an example, consider the verse Johannes 14:6 "Jesus saith unto him: I am the way, the truth, and the life: no man cometh unto the Father, but by me." The Estonian equivalent of this verse is shown in (1) and the Mandarin Chinese equivalent is shown in (2). The glosses given are the glosses suggested by the automatic procedure as described in this paper. Although the glosses are not perfect, nor complete, they are incredibly helpful for a first analysis of these sentences.¹

- (1) Estonian (Uralic)
Jeesus ütleb temale: Mina olen tee ja tõde ja elu,
Jesus saith him I am way and truth and life
ükski ei saa Isa juure muidu kui Minu kaudu!
man no ? Father unto ? ? I by

¹ B. Wälchli (p.c.) informs us that the Estonian gloss does not have any errors, though the inclusion of a demoted actor phrase in passive (*minu kaudu*, 'by me') is bad Estonian. H.-J. Bibiko (p.c.) informs us that the Chinese gloss almost perfect. Only the character glossed as 'but' does not mean *but*.

- (2) Mandarin Chinese (Sino-Tibetan)
耶穌說我就是道路、真理、生命；
Jesus saith I ? am way truth ? life
若不藉著我，沒有人能到父那裡去。
? but by ? I no man ? ? father ? ? ?

This paper is organised as follows. First, there is some general discussion on our approach to automatic alignment. In Section 2, we present a short survey of the problem of automatic word-by-word alignment. In Section 3, the fundamental principle of our approach to this problem is presented, viz. *co-occurrence statistics*, which is based on the assumption that words are linked, when they are often found together in a corpus of a particular language. Then, in Section 4, we discuss how these statistics can be used for alignment between different languages. The basic idea is to count co-occurrences in the same sentences between two different languages. Such count will be called *trans-co-occurrences*.

The second part of this paper presents an application of this method. Here, we attempt to align different translations of the Bible. In Section 5, we describe how we extracted a sentence-by-sentence alignment from Bible translations, and how we prepared such translations for our analysis. In Section 6, the sentence-by-sentence alignment is turned into a word-by-word alignment using trans-co-occurrences. Finally, in Section 7 the resulting word alignments are evaluated using a concordance-method as used in Bible exegesis: the so-called Strong's Numbers. The results of this evaluation are promising, suggesting that our approach to the alignment of parallel texts is worthwhile, and should be pursued further.

2. Word alignment

The task of word alignment is to link words in a text to its correspondences in the translated text in another language, so that the connected words supply the same contents. Computational proposals for this problem have been made starting in the late 1980's (cf. Véronis 2000 for a survey). For most parallel texts, the problem already starts with the alignment of sentences. Given a text and its integral translation, which sentence in language *B* is to be considered the translation of a sentence in language *A*? Much of the literature on automatic alignment deals with this problem. However, for our current task of aligning bible translations, the sentence alignment is already provided in the form of verse numbering, which is included in all bible translations (cf. Section 5 for more details). The task thus is reduced to producing word-by-word linkage on the basis of given sentence-by-sentence alignment.

The forms of linkage attested varies depending on the typological structure of the languages in the pair and on the freedom of translation taken in the construction of the parallel texts. An example of word-by word alignment is presented in Figure 1, following the examples and analysis by Brown et al. (1990; 1993). The most common type is a *1:1* associations, like between *The* and *Les* in the figure. In this case

we can assume that the meaning of both words are mostly equal. In $1:0$ associations, the equivalent of a word is not present in translation, as shown for *And* in the figure. Often, words have to be associated with multiple words in the other language. This are so-called $1:n$ or $n:1$ associations, often found with compounds or fixed constructions (cf. *autochtones* in the figure). Figure 1 also highlights the worst case: a general $n:m$ alignment, where on both sides multiple words are linked together. Although it is possible to divide the chunks in smaller parts in both languages separately, this cannot be done simultaneously in a compatible way. Such general $n:m$ alignments will occur with high frequency when two rather strongly agglutinating or polysynthetic languages are aligned.

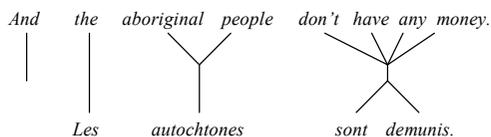


Figure 1. An alignment between English and French.

In this paper, we will approach the problem of word alignment using co-occurrence statistics. This method has, to our knowledge, not been attempted for the alignment of parallel texts. The research reported on here is only a first attempt at using this method for this goal, and there are various improvements possible. However, even with the rather basic implementation used here, we are already getting fairly good results, suggesting that this approach is worthwhile pursuing.

3. Using co-occurrence statistics

The goal of co-occurrence statistics is to extract pairs of words from a corpus that are associated in any kind of way. The underlying assumption is that while generating text, people are complying to syntactic and semantic restrictions of their natural language in order to produce correct sentences. When analyzing a large quantity of text (a text corpus), words that tend to appear together will reflect these linguistic restrictions. While it is generally possible to produce sentences containing arbitrary pairs of words, in most of the cases the words appearing together will have something to do with each other and statistics will be able cut out the noise.

The joint occurrence of words within a well-defined unit of information, for example the sentence, a whole document, or a word window,² is called a co-occurrence. The simplest co-occurrence statistics would be to count how often two

² A *word window* is a stretch of text defined relative to a central word X within a given window size S . The word window around X consists of all words occurring next to X up to maximally S words away. For example, the window of size three around the word 'text' as occurring in the first line of this footnote, consists of the words {a, stretch, of, defined, relative, to}.

words co-occur within all units of information in the corpus. However, because more frequent words have higher probabilities in appearing together with any word, just because they are frequent, this will not give meaningful associations. Therefore, a significance measure is applied that takes the single word frequencies as well as their joint frequency into account. In our experiments, we use a log-likelihood measure that, intuitively speaking, measures the amount of surprise to see two words co-occurring together as often as they do, compared to the statistical expected number of co-occurrences if we assume independence of occurrence. In this paper, the significance values for the co-occurrence of two words A and B are calculated according to the formula as shown in (3), cf. Biemann et al. (2004a).

$$(3) \quad sig(A,B) = \frac{x - k \log x + \log k!}{\log n}$$

n = number of units of information in the corpus
 k = number of joint occurrences of A and B within a unit of information
 $x = ab/n$
 a = number of occurrences of A in the corpus
 b = number of occurrences of B in the corpus

The significances are computed for every pair of words in the corpus. The significance values give us the possibility to rank the co-occurrences of a given word, as higher significance values denote a higher degrees of association. Normally, such statistics are applied on monolingual corpora, and the results are semantic nets. Semantically related words tend to show a high degree of association.³

4. Trans-co-occurrences

When applying co-occurrence analysis to multi-lingual parallel texts, we are interested in the association between pairs of words, each from a different language. In that usage, co-occurrence statistics can automatically extract translational equivalents of words, given a sentence-aligned bilingual corpus. Given a sentence translation pair we merely calculate significant co-occurrences between words from different languages and call them *trans-co-occurrences*. If a word A in the first language is always translated into B in the second language, then B will be the highest ranked trans-co-occurrence of A . Further, A will have more lower-ranked trans-co-occurrences with much smaller significance values, the highest of which normally represent alternatively possible translations. In this general case, there are several possibilities to translate a word from the first language into a second language. In this setting, the most prominent translation will be ranked highest, followed by less prominent translations and finally noise.

³ This property can be used to create semantic networks for short texts or spoken language streams as discussed in Biemann et al. (2004b)

Given the data obtained by trans-co-occurrence statistics, it is possible to construct dictionaries from parallel texts in a fully automatic way: All trans-co-occurrences above some significance threshold will be entered in the dictionary. The quality as compared to manually compiled dictionaries can be estimated at 60%–80% correctness (Sahlgren 2004, Biemann & Quasthoff forthcoming). However, we are currently not interested in building up dictionaries, including all possible meanings of a particular word, but in word-by-word alignment between two given translational equivalents; in our case of the Bible.

5. Preparations: sentence alignment and markup

For our research, we used Bible translations from the SWORD PROJECT as parallel corpora.⁴ To calculate the trans-co-occurrences, two bibles were merged to a new bilingual bible. Using the Bible's verse numbering as anchors, we combined corresponding sentences to a new longer sentence through concatenation. In principle, we could have simply concatenated whole verses, but we decided to try to restrict the information unit because we were afraid that verses would be too long to yield significant co-occurrences.⁵ We tried to restrict the information unit to, roughly, the size of a sentence. To achieve this, we first splitted verses into smaller parts, using full stops and semicolons as separators. If the number of parts obtained is identical for the two languages, then we splitted the verse. However, if the number of parts is not identical, we kept to the complete verse. For example, consider the verse Genesis 1:2 in the English King James Version (KJV) and the German Luther translation as shown in (4).

- (4) a. And the earth was without form, and void;
and darkness was upon the face of the deep.
And the Spirit of God moved upon the face of the waters.
b. Und die Erde war wüst und leer, und es war finster auf der Tiefe;
und der Geist Gottes schwebte auf dem Wasser.

As can be seen from this example, after splitting the verse the number of obtained parts differs between the two languages. The English version (4a) consists of three parts, but the German translation (4b) only consists of two parts. So in this case, we are unable to restrain the information unit. The whole verses are simply concatenated into a bilingual sentence, as shown in (5). For the automatic distinction of the languages, each word was marked with language-identifying tags, like '@en' for English or '@de' for German, as shown in (6).

⁴ <http://www.crosswire.org/sword/index.jsp>

⁵ With hindsight, seeing the results of our investigation, we now think that this step was not necessary. The algorithm that we have used seems to be robust enough to cope with longer information units, like whole verses of the Bible. However, it is expected that using larger information units requires more instances (i.e. parallel units) to get reliable statistics.

- (5) And the earth was without form, and void; and darkness was upon the face of the deep. And the Spirit of God moved upon the face of the waters. Und die Erde war wüst und leer, und es war finster auf der Tiefe; und der Geist Gottes schwebte auf dem Wasser.
- (6) And@en the@en earth@en was@en without@en form@en and@en void@en and@en darkness@en was@en upon@en the@en face@en of@en the@en deep@en And@en the@en Spirit@en of@en God@en moved@en upon@en the@en face@en of@en the@en waters@en Und@de die@de Erde@de war@de wüst@de und@de leer@de und@de es@de war@de finster@de auf@de der@de Tiefe@de und@de der@de Geist@de Gottes@de schwebte@de auf@de dem@de Wasser@de

Following this approach, two bible translations can be combined into one language-tagged bilingual bible. This bilingual text can then be used to compute the trans-co-occurrences for each word.⁶

6. Algorithm for word alignment

Using the trans-co-occurrence statistics, any word in a particular sentence from the bible will now be linked to a word in the other language. To demonstrate our approach to such word alignment, consider the verse Lucas 11:4, as shown in (7) – the English KJV translation in (7a) and the German Luther version in (7b).

- (7) a. And lead us not into temptation; but deliver us from evil.
b. Und führe uns nicht in Versuchung, sondern erlöse uns von dem Übel.

From this verse, we have selected the English words *temptation* and *deliver* as exemplars. The German trans-co-occurrences of these English words are tabulated in Table 1 and Table 2, respectively. These tables are based on the whole bible, so all kind of words do occur, irrespectable of the actual words that are found in the German version of the verse Lucas 11:4. (The words that occur in this verse are printed in boldface in the tables). If we would simply take the highest ranked word that is present in the German sentence as the best match, then the English *temptation* is correctly linked to the German *Versuchung*. However, as can be seen from Table 2, the English *deliver* is then wrongly linked to the German *nicht*. The pair (*deliver*, *nicht*) has a higher significance value than the correct pair (*deliver*, *erlöse*).⁷ This error regularly occurs with highly frequent words like *nicht* or *in*.

The basic idea to alleviate this problem is to combine the ranks of the significance statistics looking from English to German with the statistics when looking from German to English. For example, the English *deliver* suggested *nicht* as the

⁶ The procedure to compute the (trans-)co-occurrences is described in detail in Biemann et al. (2004a).

⁷ In regular dictionaries, the translational pair *deliver-erlöse* is not found. So, if we manage to deal with such cases, we are actually improving on sugin dictionaries.

best match (on rank 15). However, when we look at the trans-co-occurrence statistics for the German word *nicht*, the English word *deliver* is only ranked as match number 44. In contrast, for the German word *erlöse*, the English word *deliver* ends up as the highest ranked trans-co-occurrence, though it was only ranked on number 19 in Table 2. The pair (*deliver*, *nicht*) has thus ranks 15 and 44, which seems intuitively worse than the pair (*deliver*, *erlöse*) with ranks 19 and 1.

Table 1. Ranked German trans-co-occurrences of the English word *temptation*. A selection of the words occurring in the German version of Lucas 11:4 are printed in boldface.

rank	word	overall corpus frequency	number of co-occurrences	co-occurrence significance
1	Versuchung	10	9	59
2	fallet	6	4	26
3	Anfechtung	8	4	25
4	verstocket	4	2	13
5	betet	39	3	13
...				
7	erlöse	12	2	11
10	Übel	61	2	8
12	nicht	7541	11	7

Table 2. Ranked German trans-co-occurrences of the English word *deliver*. A selection of the words occurring in the German version of Lucas 11:4 are printed in boldface.

rank	word	overall corpus frequency	number of co-occurrences	co-occurrence significance
1	erretten	79	71	260
2	errette	37	34	126
3	Hand	1052	79	109
4	Hände	408	45	78
5	geben	592	47	68
...				
15	nicht	7541	117	27
19	erlöse	12	7	24
22	uns	1525	39	22
59	führe	42	5	10
70	Versuchung	10	3	9

We formalized this intuition by defining a MATCH VALUE m for a pair of English-German words as shown in (8), based on the multiplication of the two rank-numbers.⁸ On the basis of this value we get the right match, because $m(\textit{deliver}, \textit{erlöse}) = 0.229$, which is clearly better than $m(\textit{deliver}, \textit{nicht}) = 0.039$.

$$(8) \quad m(e, g) = \frac{1}{\sqrt{\textit{rank}_e(g) \cdot \textit{rank}_g(e)}}$$

In this way, the best translational equivalent for a particular word can be found with rather great precision (see the next section for an evaluation of this approach).⁹ However, the match value is even more informative because the height gives an indication of how good is the best match that is found. The best possible result is achieved when the matched words are both the highest ranked trans-co-occurrences. Both ranks are then one, and the resulting match value m is 1.00. If the matched pair is less directly equivalent, the match value will be lower (cf. $m(\textit{deliver}, \textit{erlöse}) = 0.229$ as discussed above). The height of this value can be used to select only the best translations. Allowing also lower valued matches, more words are actually linked to a translation. However, there will also be some more errors included. This trade-off is investigated in the next section.

7. Using Strong's Numbers as a benchmark

To evaluate the results of our algorithm, we used the so-called 'Strong's Numbers' that are available in some bible translations. These numbers are annotations added to a bible text following a system devised by James Strong in the 19th century. James Strong (1822-1894) was professor of exegetical theology at Drew Theological Seminary (Madison, New Jersey). Under his guidance, an exhaustive concordance between the King James Version (KJV) of the Bible and the Hebrew Old testament (i.e. the Masoretic Text, called *Tanakh* in Hebrew) and the Greek New Testament (i.e. the *Textus Receptus*) was compiled, apparently with the help of more than a hundred unnamed colleagues. This work first appeared in 1890. This concordance is based on a dictionary of all words occurring in the Hebrew and Greek bibles, which are numbered along their alphabetical order. These num-

⁸ Note that the use of the square root in this formula is basically irrelevant, as we are only interested at the relative ordering of the resulting m values, and not at their absolute magnitude. However, the square root prevents the m values from becoming small very quickly, which might lead to many, possibly confusing, decimal zeros.

⁹ The resulting tables of trans-co-occurrences are a highly valuable resource for other projects as well. Note, for example, that it is also possible to use the trans-co-occurrence statistics, as obtained by analysis of the bible, for the translation of other, yet untranslated texts. However, we can not use the bidirectional match value in that case, but only the ranking as implicit in the trans-co-occurrence statistics.

bers are then inserted in the English text of the KJV. Following this example, these numbers were later also added to various other translations of the bible.

As an example, consider the verse Revelation of John 1:8 from the New Testament in the KJV translation, as shown in (9). The Greek letter *A*, translated into English as ‘Alpha’, is the first entry in the Greek alphabetical listing. Accordingly, the word ‘Alpha’ in the KJV translation is marked with the number <1> behind it. The main difference between these Strong’s Numbers and a modern XML-style mark-up is that the Strong Numbers only marks the end of the entry and not the start. This leads to some problems for the automatic processing, because it is not clear exactly to which part a Strong Number refers. For example, the words *is to come* in the quotation below are not individually marked by a Strong’s Number, but only as a group. In most cases, the Strong’s Number appears to be placed immediately following the main lexical equivalent of the word in the Greek or Hebrew text. We decided to include only this last word before a Strong’s Number for the evaluation of our algorithm. Also note that in some cases there are multiple Strong’s Numbers associated with one part of the English translation (cf. the same phrase *is to come*, associated with the numbers 2064 and 3801). This situation arises because in some cases there are multiple words in the Greek or Hebrew texts which are translated as just one word or phrase into English. We included both numbers for testing the results of our algorithm.

- (9) I <1473> am < 1510> **Alpha <1>** and <2532> Omega <5598>, the beginning <746> and <2532> the ending <5056>, saith <3004> the Lord <2962>, which <3588> is <5607, 3801>, and <2532> which <3588> was <2258, 3801>, and <2532> which <3588> **is to come <2064, 3801>**, the Almighty <3841>. (KJV, Rev. 1:8)

When two translations of the Bible are both marked with Strong’s Numbers, then these numbers can be used to evaluate an automatically generated alignment. There are four different situations that can occur when comparing the automatic alignment with the Strong’s Numbers:

- **Correct:** the aligned words are both followed by a Strong’s Number, and these numbers are identical (in case there is only one number) or show an overlap (in case there are multiple numbers)
- **Error:** the aligned words are both followed by a Strong’s Numbers, but these numbers are different (in case there is only one number) or do not show any overlap (in case there are multiple numbers)
- **One-sided miss:** only one of the aligned words is followed by a Strong’s Number, but the other is not.
- **Uninformative:** both aligned words are not followed by a Strong’s Number.

As an example, compare the KJV translation in (9) with the German translation by Luther in (10). If the automatic alignment would align the English *I* to the German *Ich*, this would be counted as correct because both are followed by the same Strong’s Number <1473>. However, if it would align *am* with *ich*, this would

clearly be an error, as the words are followed by different Strong’s Numbers. One-sided misses occur for example when the English *Lord* would be (correctly) aligned with *Gott*. Although this is correct, this alignment cannot be validated because there is no Strong’s Number directly following the German *Gott*. From some random inspection of such cases, we suspect that the far majority of such one-sided misses are actually correct alignments that are obscured by the specific placement of the Strong’s Numbers in the text. Finally, there are alignments that cannot be interpreted because both words are not followed by a Strong’s Number. For example, the articles, like *the* and *der*, are both not followed by a strong number, and are thus uninformative for the evaluation.

- (10) Ich <1473> bin <1510> das A <1> und <2532> das O <5598>, der Anfang <746> und <2532> das Ende <5056>, spricht <3004> Gott der HERR <2962>, der <3588> da ist <3801> und <2532> der <3588> da war <2258> <3801> und <2532> der <3588> da kommt <2064> <3801>, der Allmächtige <3841>. (Luther, Rev. 1:8)

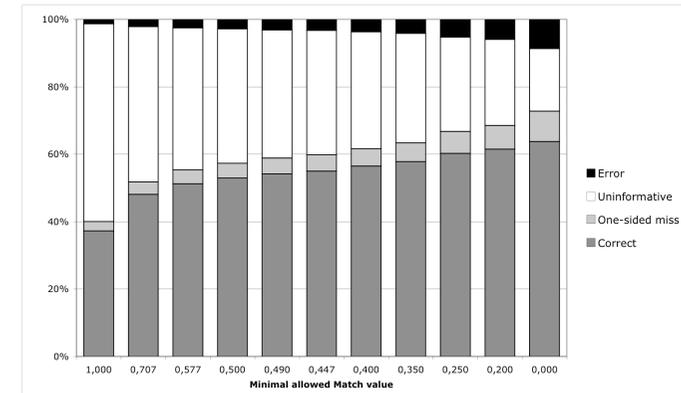


Figure 2. Evaluation of English-German Alignment

The actual number of errors and correct alignments depends on the MATCH VALUE $m(e,g)$, as defined in the previous section. The match value gives an indication how good the algorithm evaluates a particular alignment of two words between the translations. An alignment with the highest possible match value of 1.00 means that this is probably a good match; a lower match values indicates less confidence. In Figure 2, we show the evaluation of the English (KJV) - German (Luther) alignment, depending on the allowed match values. In the first column, only the alignments with a match value of 1.00 are shown. As can be seen in the figure,

more than 50% of these alignments are uninformative. If lower match values are allowed, this portion becomes smaller, but also the number of errors increases.

In general, the less constrained we are concerning the inclusion of automatic alignments, the more correct matches we get, but also the more errors are included. To show this trade-off between accuracy and overall performance, we defined measures for precision and recall on the basis of these validations, as shown in (11). These values for precision and recall are very conservative and thus very probably lower than the actual performance of the automatic alignment. We expect that most of the one-sided misses and many of the uninformative cases are actually correct alignments. However, we have no way to assess that more precisely at this point.

$$(11) \begin{aligned} \text{Precision} &= \text{correct} / (\text{correct} + \text{error} + \text{one-sided miss}) \\ \text{Recall} &= \text{correct} / \text{all alignments} \end{aligned}$$

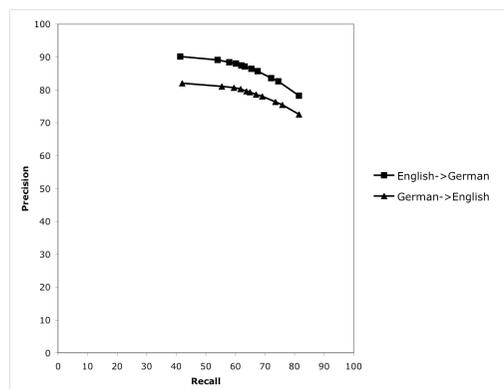


Figure 3. Trade-off between precision and recall for the English-German alignment

We computed the precision and recall for every match value (i.e. for every column in Figure 2). The resulting values are plotted in Figure 3, connected by a line. There are two lines shown in this figure because we performed the alignment directionally. One line in the figure represents the precision and recall for the direction where we started with the English translation and then tried to find the best match in the German translation. The other line represents the inverted procedure. Interestingly, the precision from English to German is better than the other way around, although the recall roughly remains the same. This is probably caused by the fact that German has more morphology than English, and consequently the German translation has less words. The resulting major difference is that the number of

one-sided misses is clearly higher for the direction German to English when compared to the direction English to German.

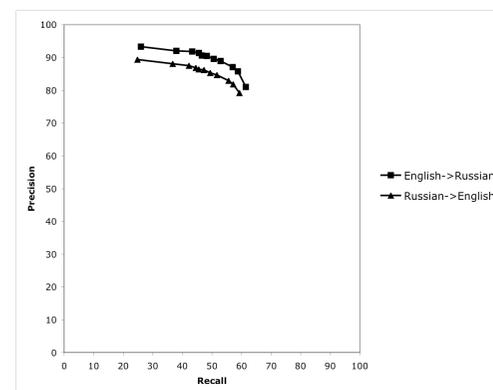


Figure 4. Trade-off between precision and recall for the English-Russian alignment

We performed the same evaluation for the alignment of the English KJV translation with the Russian ‘Synodal’ translation from 1876. The results of the evaluation using the Strong’s Numbers is shown in Figure 4. The precision is comparable to the English-German alignment, but the recall is much worse. This is the result of a much higher fraction of uninformative alignments, though we have no real answer why the number of uninformative alignments would be higher between English and Russian than it was between English and German.

Finally, we also evaluated an English-Chinese automatic alignment by using the Chinese ‘Traditional Union’ translation, which has also been annotated by Strong’s Numbers. The results of our evaluation are shown in Figure 5. The first aspect to take note of is the large discrepancy between the two directions of alignment. The alignment from English to Chinese is much worse than the alignment from Chinese to English, although for the alignments with German and Russian this direction even performed slightly better. The reason for this large discrepancy is that we did not parse the Chinese text for words.¹⁰ The algorithm simply looked for the best match between any Chinese character and any word in the English text. However, most lexical words in the English text is translated by multiple Chinese characters. Now, for the evaluation of our algorithm we also took the first Chinese character before any Strong’s Number. If we start from an English word followed by a Strong’s Number, the best match will very often not be the Chinese character di-

¹⁰ Of course, this could rather easily be done, e.g. by <http://www.mandarintools.com/segmenter.html>.

rectly in front of the Strong's Number, but one of the other characters that also are part of the translation. As a result, we get a very high proportion of one-sided misses for the direction English to Chinese, which diminishes the precision. In contrast, for the direction from Chinese to English, the precision is roughly on the same level as for the alignment from German to English. The recall is worse because of a much higher proportion of uninformative matches.

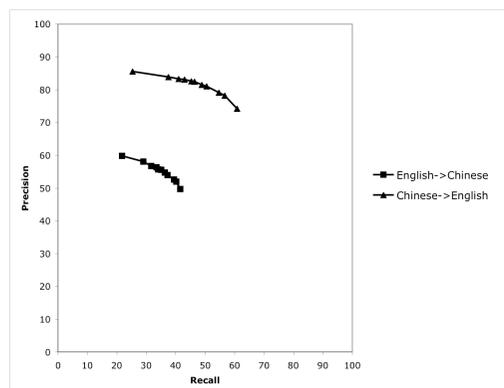


Figure 5. Trade-off between precision and recall for the English-Chinese alignment

This directional difference with the Chinese-English alignment suggests an interesting consequence for the alignment between English and morphologically more complex languages (and that is why we did not parse the Chinese text for words). On an abstract level, English could be considered a much more agglutinative language than the Chinese script, as most English words map onto multiple Chinese characters. Of course, such a comparison does not make any sense linguistically. However, this way to look at it argues that the results from our alignment between English words and Chinese characters might be interpreted as showing what would happen if we would try to align English to a more agglutinative language. Starting from the morphologically more complex language is difficult (i.e. English to Chinese). However, using the alignment from the more isolating language to the more agglutinative language seems to give relatively good results (i.e. from Chinese to English), even though the structure of the languages are very different. Of course, it would be better to check this claim by actually trying to align the English text to a language with a more complex morphology. Our algorithm does have no problem providing an alignment between English and, say, the Swahili New Testament (which is also available electronically as open source), but we have no way to automatically check such an alignment because there are no

Strong's Number added to the Swahili translation (nor to any other translations of morphologically more complex languages).

8. Conclusions

The usage of trans-co-occurrences is a highly promising method to establish translational equivalents in a parallel texts. Even in the simple and straightforward version that we used in this paper, the results are already fairly good. At least good enough to provide typologists with an approximate gloss of a stretch of text, which can then subsequently be analysed in more detail by hand.

An important characteristic of our method, which makes it even more interesting for typology, is that there is no knowledge needed at all. The only information that is assumed is an aligned information unit (in our case, the Bible verses) and a word-separator (we simply used the occurrence of spaces). However, one could easily improve this method by adding information—also possibly extracted automatically. For example, instead of a word-by-word alignment, a morpheme-by-morpheme alignment can be attempted, presupposing that we know about the morpheme separation of both languages. In the other direction, another possible enhancement would be to mark frequent collocations in each language—and not align the individual words, but whole chunks of possible idiomatic expressions.

In contrast, instead of adding information beforehand, it is also possible to use the trans-co-occurrences (as, for example, extracted from Bible translations) for further linguistic analysis. For example, it turns out that morphological variations of the same root often occur together in the trans-co-occurrences (cf. *erretten/errette* and *Hand/Hände* in Table 2). This suggests that the trans-co-occurrence statistics might also be used to investigate the morphological structure of a language. However, all these suggestions are left for further research.

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