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Strunk, J.; Schiel, F.; Seifart, F.C.

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Untrained Forced Alignment of Transcriptions and Audio for Language Documentation Corpora using WebMAUS

Jan Strunk, Florian Schiel, Frank Seifart

University of Amsterdam, Bavarian Archive for Speech Signals (BAS), University of Amsterdam
j.strunk@uva.nl, schiel@bas.uni-muenchen.de, F.C.Seifart@uva.nl

Abstract
Language documentation projects supported by recent funding initiatives have created a large number of multimedia corpora of typologically diverse languages. Most of these corpora provide a manual alignment of transcription and audio data at the level of larger units, such as sentences or intonation units. Their usefulness both for corpus-linguistic and psycholinguistic research and for the development of tools and teaching materials could, however, be increased by achieving a more fine-grained alignment of transcription and audio at the word or even phoneme level. Since most language documentation corpora contain data on small languages, there usually do not exist any speech recognizers or acoustic models specifically trained on these languages. We therefore investigate the feasibility of untrained forced alignment for such corpora. We report on an evaluation of the tool (Web)MAUS (Kisler et al., 2012) on several language documentation corpora and discuss practical issues in the application of forced alignment. Our evaluation shows that (Web)MAUS with its existing acoustic models combined with simple grapheme-to-phoneme conversion can be successfully used for word-level forced alignment of a diverse set of languages without additional training, especially if a manual prealignment of larger annotation units is already available.

Keywords: word times, forced alignment, language documentation corpora

1. Introduction

1.1. Language Documentation Corpora
Recent years have seen major global efforts in the paradigm of language documentation, which aims at providing a comprehensive multimedia record of the linguistic practices of speech communities (Himmelmann, 1998, p. 166), especially of those speaking less-studied and endangered languages. Supported by large funding initiatives, such as DoBeS (Dokumentation bedrohter Sprachen) by the Volkswagen foundation, the US National Science Foundation and National Endowment for the Humanities’ Documenting Endangered Languages Program, or the Hans Rausch Endangered Languages Project, language documentation projects have created rich multimedia corpora of many different and typologically diverse languages. These language documentation corpora usually comprise audio and video recordings of spoken language, most of which have also been transcribed in a practical orthography, and often also linguistic annotations such as interlinear glossing of words and morphemes. In most recent language documentation projects, the transcription has been manually aligned with the audio and/or video material at the level of relatively large units, such as utterances, sentences, intonation units, or paragraphs, while legacy data may consist of recordings and transcriptions separately without any kind of alignment between them. These spoken-language corpora represent unique and novel resources for typological, corpus linguistic, psycholinguistic, and sociolinguistic research. Moreover, they are very valuable resources for the creation of learning tools and other language resources. Their usefulness, however, could be greatly increased with a more fine-grained temporal alignment of transcription and audio/video data at the level of words, syllables, or individual phones. This would enable novel corpus-based research which fully embodies that “language is a temporal phenomenon, a process that flows through time” (Chafe, 2002, p. 256). Manual alignment of transcription and audio at the word or even phone level would require immense amounts of time and manpower. We therefore investigate here the possibility of using automatic forced alignment in the form of the tool WebMAUS (Kisler et al., 2012) in order to obtain a word-level alignment of transcription and audio. Without any additional training on the specific languages of our corpora, WebMAUS produces quite encouraging alignment results that we consider to be of sufficiently high quality for use in actual linguistic analyses.

1.2. Practical Use Case: A DoBeS Comparative Corpus Analysis Project
The comparative corpus analysis project “The relative frequency of nouns, pronouns, and verbs cross-linguistically” (Seifart et al., 2010; Seifart, 2011), funded by the DoBeS initiative of the Volkswagen foundation, examines the ratio of nouns to verbs in corpora of several typologically diverse languages; cf. Table 1. In addition to studying variations in the noun-to-verb ratio (NTVR) from a typological perspective, correlating it with typological characteristics of a language such as the extensiveness of argument indexing and its basic word order, and from a sociological and stylistic perspective, taking speaker characteristics and text genres into account, this project also examines the development of the NTVR in real time as narrative texts and conversations unfold. Pilot studies reported in Seifart et al. (2010) and Seifart (2011) have revealed a characteristic temporal pattern with a relatively high noun-to-verb ratio at the beginning of texts and subsequent sinusoidal alternations as the narrative unfolds. We also investigate possible correlations between the NTVR and processing ease as reflected in speech rate. The existing manual segmentation and align-
Table 1: Languages investigated in the noun-to-verb ratio project

| Language          | Affiliation | Region            | Speakers | Words | Source                  |
|-------------------|-------------|-------------------|----------|-------|-------------------------|
| Baure             | Arawakan    | West Amazon       | 55       | 27,907| Swintha Danielsen et al.|
| Bora              | Boran       | North-West Amazon | 1,500    | 29,539| Frank Seifart           |
| Chintang          | Sino-Tibetan| Himalaya          | 4,500    | 37,050| Balthasar Bickel et al. |
| Even              | Tungusic    | Siberia           | 300      | 36,665| Brigitte Pakendorf       |
| Hoocâk            | Siouan      | USA               | 200      | 23,503| Iren Hartmann et al.    |
| Njuiu             | Tuu (South. Khoisan) | South Africa | 6       | 32,126| Tom Güldemann et al.    |
| Sakha             | Turkic      | Siberia           | 360,000  | 30,850| Brigitte Pakendorf       |
| Sri Lanka Malay   | Austronesian| Sri Lanka         | 45,000   | 13,044| Sebastian Nordhoff      |
| Texitstep Popoluca| Mixe-Zoquean| Mexico            | 100      | 24,674| Sören Wichmann          |

2. Automatic Forced Alignment

2.1. Previous Work

Untrained forced alignment of individual phones has already been explored with encouraging results for isolated words in a Mixtec corpus by DiCanio et al. (2013). Unlike this study, we present and evaluate a method to obtain accurate word start and end times for words in the context of complete spoken texts (that are up to one hour long) based on the WebMAUS service of the Bavarian Archive for Speech Signals (BAS) (Kisler et al., 2012).

2.2. The WebMAUS Automatic Alignment System

The Munich AUtomatic Segmentation system (MAUS) and the corresponding CLARIN web service WebMAUS combine simple forced alignment based on Hidden Markov Modeling (HMM) with optional additional statistical modeling of possible pronunciation variants for several languages. The aligner has the task to find the best partitioning of the speech signal given a statistical pronunciation model and a set of pre-trained acoustical models (HMM) for each phoneme class of a language. Forced alignment works very well granted that the signal is of moderate good quality and the truly spoken phones are known a priori, that is, the input transcription is relatively accurate. (Web)MAUS extends the basic HMM aligner concept by modeling a statistical space of possible pronunciation variants for a given orthographic input (Schiel, 1999; Schiel, 2004). For known languages, the hypotheses space is calculated for each individual text input based on a machine-learned statistical expert system of pronunciation (Schiel et al., 2011). Combined with HMM technology, the MAUS can thus not only find the best segmentation but at the same time the most likely sequence of truly spoken phones in the speech signal. On a subset of spontaneous German speech in the Verbmobil corpus (Burger et al., 2000) the MAUS technique yielded about 97% of the average interlabeler agreement of three trained phoneticians working on the same task (Kipp et al., 1996). MAUS is implemented as a system of UNIX script files and C++ binaries that can be run on Linux and Windows platforms. It requires as input the speech signal and some form of either orthographic or phonological transcript of the spoken utterance. The result is stored in either the Web Partitur Format BPF (Schiel et al., 1998), praat TextGrid or Emu (Bombien et al., 2006) compatible annotation format files. MAUS currently (version 2.68) supports 11 languages: German, Polish, Portuguese, English, Australian English, New Zealand English, Hungarian, Italian, Estonian, Spanish, Dutch, and a special language independent mode called ‘sampa’, that allows the segmentation of arbitrary languages encodedable in SAM-PA. A vast number of options allow the user to control the alignment process as well as the form of output formatting and the statistical modeling of the pronunciation variation. The MAUS freeware package can be downloaded from the Bavarian Archive for Speech Signals; a web interface to a server based implementation called WebMAUS is also available (Kisler et al., 2012).

2.3. Specific Forced Alignment Procedure

Since we are dealing with small endangered languages in our comparative corpus analysis project, for which WebMAUS has no pretrained models of pronunciation variation, we use it in a simple mode based only on HMM forced alignment without modeling possible pronunciation variants. For all the results reported throughout this paper, we used the special ‘sampa’ mode of WebMAUS, which combines the acoustic models of languages that MAUS currently supports, in order to have as large a phonetic inventory as possible for the alignment of our diverse set of languages. We thus do not carry out any training or adaptation of WebMAUS to the specific languages in our corpus. A schematic of the workflow we use for forced alignment in our project is given in Figure 1. The first step required in forced alignment is grapheme-to-phoneme conversion, that is, the conversion of the original orthography of the

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3 http://www.bas.uni-muenchen.de/forschung/Bas/software/
4 http://clarin.phonetik.uni-muenchen.de/BASWebServices/
transcriptions into a phonemic transcription suitable for the aligner used. Since we are dealing with languages for which WebMAUS does not provide ready-to-use phoneme-to-grapheme conversion modules, we perform this step ourselves using very simple transducers. Specifically, we use a short ordered sequence of simple search-and-replace rules to remove capitalization, delete punctuation marks, and to convert every grapheme in the orthographic transcription of the respective language into the SAM-PA inventory provided by WebMAUS’ special ‘sampa’ mode. This inventory includes a large part of the IPA inventory but no click sounds, for example, which occur in one of our corpora, namely the N|uu corpus, or specific models for retroflex stops required for the phonology of Sri Lanka Malay (SLM) (cf. section 3.2.). The grapheme-to-phoneme conversion is thus an approximation limited by the set of acoustic models provided by WebMAUS and based on intuitions about acoustic and articulatory similarity. It is carried out using a Python script that also converts the input corpus session files, usually Toolbox files, typically used in language documentation projects, or ELAN files (Wittenburg et al., 2006), to the input BAS Partitur Format BPF of WebMAUS (Schiel et al., 1998). An example of an automatic conversion from Bora practical orthography into the SAM-PA representation used by WebMAUS is given in figure 2. The rightmost column also provides an IPA transcription for comparison.

In the second step, the converted transcription and the corresponding audio file are then uploaded to the WebMAUS web service. We use the ‘General MAUS’ variant of WebMAUS with the SAM-PA language, no modelling of pronunciation variants (option ‘Canonly’ set to true) and BPF output format (option ‘mau-append’). Depending on whether we would like to constrain the alignment process on the basis of a pre-existing manual alignment at the level of larger units, such as paragraphs, sentences, or intonation units, or not (see below), we set the option ‘Usetrn’ to true for constrained alignment and to false for unconstrained alignment. The other available options are left at their default values.

The result output by WebMAUS, also in BAS Partitur Format, with alignment on the phoneme-level is then converted back to Toolbox or ELAN format using another set of Python scripts. Since we are currently interested in the alignment of whole words, in the third step, we reconstruct the start and end times of words from the alignment of individual phones provided by WebMAUS and finally integrate these word times directly into the session files in the case of ELAN files or store them in word-level tiers in Toolbox files for later statistical analysis.

### 3. Evaluation

In this section, we report on three studies in which we have evaluated the feasibility of using WebMAUS for the untrained forced alignment of language documentation corpora. The first study discussed in section 3.1. compares the performance of WebMAUS on eight small texts from five different languages to differences between two human aligners. Section 3.2. contains a more practical evaluation of WebMAUS as we have actually used it to align transcriptions and audio for the corpora in our NTVR project. Last but not least, we test WebMAUS on a larger corpus of Hooćak recordings which were manually aligned at the word-level independently of our project (section 3.3.). Throughout this section, we compare what we call ‘unconstrained’ and ‘constrained’ forced alignment. Unconstrained alignment only provides WebMAUS with the audio data and the transcription itself and no additional information about where to look for particular words. WebMAUS therefore tries to align the given sequence of words from the transcription in strict linear order from the start of the audio file to its end. Unconstrained alignment could, for example, be used to align legacy recordings with their separately stored transcriptions. This mode of alignment can be problematic for transcriptions with gaps of non-transcribed stretches of the audio recording or for transcriptions of dialogs with overlapping turns (since words from overlapping turns are normally not interleaved in the correct order in tools such as Toolbox) (cf. section 4.).
poration, the transcription is often already aligned with the audio recording as part of the transcription process (for example, in ELAN), albeit in larger annotation units, such as utterances, intonation units, sentences, or paragraphs. Constrained alignment provides WebMAUS with the start and end times of such pre-existing manually aligned annotation units and thus with information about the time stretches in which to search for particular words. This alignment mode is suitable for most recent corpora of spoken language that already contain explicit links between parts of the transcription and stretches in the audio recording. Since WebMAUS allows for a pre-segmentation with overlapping chunks, constrained alignment can also be used to align words when the contributions of several speakers overlap.

3.1. Evaluation on Small Test Corpora in Comparison to Differences between Two Human Aligners

Before we decided to use WebMAUS for the forced alignment of our entire NTVR project corpus (cf. section 3.2.), we carried out a small evaluation study in order to test its performance with data from several languages and with texts that we deemed relatively easy as well as with texts that we regarded as relatively hard to align. For three languages, namely, Baure, Bora, and Even, we tested WebMAUS with one ‘easy’ text and one ‘hard’ text each. The ‘easy’ texts are simple monological narrative texts with a reasonably good audio quality and few background noises; the ‘hard’ texts contain contributions from several speakers, including overlaps, as well as background noises (such as traffic or animals) and, in the case of Bora, even several people cheering and screaming. For the remaining languages, German and Sri Lanka Malay, we only tested one ‘easy’ narrative text. The words in these eight texts were also manually aligned independently by two human aligners, once by the first author and once by a student assistant. In order to speed up the alignment process, the human aligners were provided with the pre-aligned larger annotation units and exactly aligned word starts and endings within these larger units. Table 2 compares the results of automatic alignment at the word-level using WebMAUS to manually aligned word start and end times for the eight test sessions. Results are given as mean, median, and maximum (unsigned) time differences measured in milliseconds (ms). Both word start and end times are included in these figures. The German results are included for comparison. They were obtained without using the grapheme-to-phoneme conversion for German provided by WebMAUS. The last three columns of Table 2 also provide mean, median, and maximum time differences between two human aligners for comparison.

Looking at the mean time differences in table 2, especially those for unconstrained alignment, one could initially get the impression that the alignment quality obtained by using WebMAUS for untrained forced alignment on ‘unknown’ languages is less than ideal. Unconstrained align-

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8Initial results of this evaluation study were already presented at the 2013 DoBeS conference in Hannover (Strunk, 2013).

9The German text was created within the project AUVIS (Audiovisual Data-Mining for Event Segmentation in Multimodal Speech Data) at the University of Cologne.

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I report the result of unparametric Wilcoxon tests here: Baure easy ($W = 746237$, $p < 0.001$), Baure hard ($W = 1159270$, $p$...
Constrained Alignment

| Test Session  | Words | Unconstrained Alignment | Constrained Alignment | Interaligner Differences |
|---------------|-------|-------------------------|-----------------------|--------------------------|
|               |       | mean | median | max   | mean | median | max   | mean | median | max   |
| Baure (easy)  | 502   | 15,312 ms | 300 ms | 116,810 ms | 160 ms | 101 ms | 1,030 ms | 115 ms | 0 ms | 1,063 ms |
| Baure (hard)  | 689   | 1,100 ms | 139 ms | 18,361 ms | 204 ms | 60 ms | 3,214 ms | 86 ms | 48 ms | 1,932 ms |
| Bora (easy)   | 289   | 1,455 ms | 50 ms | 25,496 ms | 148 ms | 30 ms | 3,338 ms | 76 ms | 45 ms | 910 ms |
| Bora (hard)   | 108   | 6,460 ms | 8,020 ms | 12,995 ms | 290 ms | 160 ms | 1,485 ms | 162 ms | 66 ms | 1,398 ms |
| Even (easy)   | 405   | 696 ms | 37 ms | 12,833 ms | 196 ms | 34 ms | 2,272 ms | 57 ms | 26 ms | 745 ms |
| Even (hard)   | 236   | 612 ms | 183 ms | 5,820 ms | 248 ms | 63 ms | 2,589 ms | 59 ms | 30 ms | 1,193 ms |
| German (easy) | 467   | 131 ms | 31 ms | 3,172 ms | 42 ms | 32 ms | 770 ms | 25 ms | 17 ms | 170 ms |
| SLM (easy)    | 204   | 297 ms | 38 ms | 6,180 ms | 207 ms | 41 ms | 6,127 ms | 104 ms | 41 ms | 2,607 ms |

Table 2: Time differences between automatic alignment using WebMAUS and human aligners (word start and end times)

terannotator differences are also significantly smaller than the differences between one human annotator and the results of constrained alignment, except again for the Sri Lanka Malay session where the test fails to reach significance.11 Even though WebMAUS makes use of acoustic models trained on German speech data, rather than speech data from Baure, Bora, Even, or Sri Lanka Malay, the median time differences for these other languages seem to be roughly comparable to the results for German. Comparing constrained alignment on the easy German session to all other easy sessions, however, shows that the forced alignment results on the German session are still significantly closer to the human alignment gold standard than the other languages.12 This is probably due both to the acoustic models of WebMAUS as well as the fact that the transcription of the German session is exceptionally detailed and complete. Interestingly, the intuitive distinction between easy and hard sessions (for Baure, Bora, and Even) is only reflected in the constrained automatic alignment results, whereas, for unconstrained alignment, the accuracy and completeness of the transcription seems to be more relevant to successful alignment than the acoustic difficulty of a session (background noises, overlaps, etc.).13 The distinction also does not seem to be very relevant to human aligners.14

3.2. Evaluation on the Entire Corpus of the Noun-to-Verb Ratio Project

Based on the results of our pilot evaluation reported in the previous section, we decided to go ahead and use WebMAUS to produce a word-level alignment between audio and transcription for all texts in our entire NTVER project corpus. Because most of our subcorpora already contained a pre-existing manual alignment at the level of larger annotation units and because unconstrained alignment can easily be led astray by incomplete transcriptions and speaker overlaps, as we have seen in the previous section, we used WebMAUS in constrained alignment mode whenever possible. In the case of the Texitpec Popoluca corpus, for which there existed no previous manual alignment at all but which only contains monological narrative texts, we first used WebMAUS to carry out an unconstrained forced alignment and then, if necessary, corrected the resulting boundaries of annotation units by hand and finally reran WebMAUS in constrained alignment mode on the same sessions. In order to ensure the quality of our linguistic analyses, we also decided to manually check the automatic word alignment produced by WebMAUS using ELAN and to correct larger alignment errors by hand. We did not, however, check each and every word individually but rather listened through the recordings and only corrected the boundaries of clearly misaligned words. In this section, we compare the automatic word-level alignment produced by WebMAUS with the manually corrected version of this alignment.15 The results reported here thus do not arise from a comparison with an independently created gold-standard alignment, but rather represent a practical evaluation providing information about what percentage of automatically aligned words we deemed to be in need of correction and how far their boundaries needed to be shifted on average. Table 3 shows the percentage of words in our project corpus and its subcorpora whose boundaries (start time or end time or both) have been manually corrected and by how many milliseconds on average their boundaries were shifted. The latter figure only takes those words into account whose alignment was modified in the manual correction.

11Baure easy (W = 667506, p < 0.001), Baure hard (W = 43653, p < 0.001), Even easy (W = 352639, p = 0.009), Even hard (W = 135008, p < 0.001), German easy (W = 461580, p = 0.029), and Sri Lanka Malay easy (W = 83156, p = 0.982).

12German vs. Baure easy (W = 777309, p < 0.001), German vs. Bora easy (W = 285236, p = 0.063), German vs. Even easy (W = 426543, p < 0.001), and German vs. Sri Lanka Malay easy (W = 223143, p < 0.001).

13Constrained alignment: Baure easy vs. hard (W = 803187.5, p < 0.001), Bora easy vs. hard (W = 28816.5, p < 0.001), Even easy vs. hard (W = 158166.5, p < 0.001) all go in the expected direction. Unconstrained alignment: Baure easy vs. hard (W = 909481, p < 0.001) in the opposite direction, Bora easy vs. hard (W = 14928, p < 0.001) in the expected direction. Even easy vs. hard (W = 144785, p < 0.001) in the opposite direction.

14Baure easy vs. hard (W = 622753.5, p < 0.001) in the opposite direction, Bora easy vs. hard (W = 58068, p = 0.129), Even easy vs. hard (W = 192561.5, p = 0.827).

15At the time of writing of this paper, not all sessions in our corpus were already manually checked so that not all sessions could be used in this evaluation. This problem mostly affects the Texitpec Popoluca and Njuu subcorpora.
tion stage. Overall, 31.41% of all word alignments were corrected in the manual correction stage (word start or end time or both). This percentage of corrected word alignments varies from only 13.67% for Chintang to 68.75% for Bora. However, it is not clear that it is sensible to compare the figures for two individual languages because the manual correction work had to be carried out by several people in parallel (including the first author, Alena Witzlack-Makarevich, and several student assistants listed in section 5.), who were assigned to different subcorpora, in order to save time. It may simply be the case, for example, that the person correcting one language was a little bit more meticulous than the person correcting a different language. In general, one can probably expect a rate of about 30% manual corrections of word times on a typical language documentation corpus that provides a prealignment usable for constrained forced alignment. An interesting observation is that the percentage of corrected word times exhibits a strong positive correlation with the average size of the prealigned annotation units (AUs) in a language’s subcorpus, provided as the mean number of words per annotation unit in the third column of Table 3 ($r = 0.75$, $t = 2.55$, $df = 5$, $p = 0.05$). As one would probably expect, the number of word time corrections that are required increases as the average size of the annotation units (sentence, intonation unit, paragraph, etc.) gets larger. Smaller prealigned annotation units simply contain more information about where words are located and provide less opportunity for the forced alignment to go wrong. A rate of about 30% manually corrected word times also accords with our experience that manually aligning all word boundaries from scratch inside pre-existing larger annotation units takes at least three times more time than manually correcting automatically aligned word boundaries. In our experience, this ratio increases even more as the prealigned annotation units increase in size.

As the last three columns in Table 3 show, the mean size of the time shift of 646 ms between the automatically aligned word start and end times and the manually corrected ones again seems to be somewhat inflated by some rare extreme corrections of more than 10 seconds, which could only occur inside very large annotation units or in case the existing prealignment into annotation units was incorrect in some instances. The overall median time shift of 137 ms is a better characterization of how far word boundaries typically needed to be shifted in the manual correction stage and is also more in line with the median alignment error obtained for constrained forced alignment on the manually aligned test sessions discussed in section 3.1. above.

An interesting observation, albeit a preliminary one because manual word time corrections have only been carried for two of the included texts, is that the results of constrained alignment using WebMAUS obtained for the N|uu subcorpus compare quite favourably with the results for the other languages in table 3, both with regard to a moderate number of corrected word boundaries of 20.95% and with regard to the average time shift in case of word time corrections: The mean time shift of 194 ms and the median of 74 ms for N|uu are way below the overall mean and median time shift of 646 ms and 137 ms, respectively. These results are noteworthy, in our opinion, because the SAMPA inventory currently provided by WebMAUS lacks a lot of the typical consonants of the N|uu language, particularly different clicks, which therefore had to be mapped to other consonants contained in the WebMAUS SAMPA inventory based on vague intuitions about acoustic and/or articulatory similarity. A relatively crude grapheme-to-phoneme conversion like the one for N|uu thus does not seem to impede successful forced alignment. Neither the exactness of the grapheme-to-phoneme conversion nor the use of acoustic models trained on the specific language one wants to align therefore seem to be crucial to the success of automatic forced alignment with WebMAUS.

Finally, the two Texisteppe Popoluca texts in our corpus in which word times have already been manually corrected allow us to take a look at the average time error between unconstrained alignment and the final word start and end times obtained after manual correction of constrained alignment (this time for all wordtimes not only manually corrected ones); cf. Table 4. At least for these two sessions, unconstrained alignment worked quite well, as the overall median time error of 110 ms for word start and end times shows. But the results of unconstrained alignment vary quite a bit even between these two texts. The median time error of only 30 ms for the text “Pepito” is much smaller than the median time error of 171 ms obtained for “La Chichimeca” (Wilcoxon’s test: $W = 609477$, $p < 0.001$).

| Language | Texts | Words per AU | Words | Perc. Corrected Words | Time Shift Mean | Time Shift Median | Time Shift Max |
|----------|-------|--------------|-------|------------------------|----------------|------------------|---------------|
| Baure    | 60    | 3.72         | 28,587| 19.94%                 | 540 ms         | 206 ms           | 15,289 ms     |
| Bora     | 32    | 6.94         | 20,846| 68.75%                 | 361 ms         | 81 ms            | 15,970 ms     |
| Chintang | 52    | 3.96         | 46,599| 13.67%                 | 2,408 ms       | 377 ms           | 18,995 ms     |
| Even     | 36    | 6.94         | 22,917| 38.99%                 | 373 ms         | 147 ms           | 8,651 ms      |
| N|uu      | 2     | 4.54         | 1,642 | 20.95%                 | 194 ms         | 74 ms            | 3,060 ms      |
| Popoluca | 2     | 3.22         | 2,269 | 27.46%                 | 202 ms         | 65 ms            | 4,424 ms      |
| Sakha    | 16    | 7.30         | 30,848| 38.83%                 | 338 ms         | 100 ms           | 10,488 ms     |
| Overall  | 200   | 4.95         | 153,708| 31.41%               | 646 ms         | 137 ms           | 18,995 ms     |

Table 3: Overview of manually corrected word boundaries after constrained forced alignment of the NTVR project corpora
3.3. Evaluation on an Independently Manually Aligned Corpus of Hooc’ak Recordings

The final evaluation of WebMAUS on language documentation data that we carried out within our project is based on a corpus of Hooc’ak recordings provided to us by Iren Hartmann. Even though we hope to be able to use this corpus also in research on the noun-to-verb ratio, it has been manually time aligned at the word-level independently of our NTVR project. It thus represents a good gold standard test corpus for constrained and unconstrained forced alignment with WebMAUS. As the manual time alignment of words has been carried out in ELAN using a “Time_Subdivision” relation between annotation units and the words contained in them, which does not allow for gaps between words, instead of using the more flexible “Included_In” relation, only word start times are correctly aligned with the audio signal, while word end times automatically coincide with the start of the following word. For this reason, the evaluation results discussed in this section are based on word start times only.

Table 5 provides the results of evaluating WebMAUS on this Hooc’ak corpus using both unconstrained and constrained forced alignment. As one would expect, the mean word start and end time difference between constrained forced alignment and manual alignment is much lower than the mean time difference between unconstrained forced alignment and manual alignment: 279 ms (constrained alignment) vs. 4,279 ms (unconstrained alignment).

Interestingly, however, the median time differences are much closer together with a medium error of 60 ms in the case of unconstrained alignment compared to a medium error of 50 ms in the case of constrained alignment. This suggests that on the 41 Hooc’ak texts we could use for this evaluation, which mostly contain well-transcribed monological narratives, unconstrained forced alignment worked almost as well as constrained forced alignment, except for a few outlier cases of extreme misalignment. The maximal alignment error was over three minutes in the case of unconstrained alignment and over 21 seconds in the case of constrained alignment. The former resulted from an over three minute long but untranscribed stretch of English speech interrupting the transcribed Hooc’ak speech. Since no prealigned annotation units were located in this region of the audio file, the resulting misalignments could easily be avoided by the constrained forced alignment. The maximal alignment error in the case of constrained alignment was due to a very long annotation unit containing just two words one of which was misaligned with an untranscribed response from a listener. Such relatively rare cases of extreme alignment errors again inflate the mean time differences so that the automatic alignment results produced by WebMAUS, which we find quite impressive, particularly also those from unconstrained automatic alignment in the case of this Hooc’ak test corpus, may look unconvincing at first sight.

4. Discussion and Conclusion

Despite the incomplete inventory of phonemes and acoustic models provided by WebMAUS, our often somewhat crude grapheme-to-phoneme conversion using simple search-and-replace rules, and the use of simple HMM forced alignment only, our experiments with WebMAUS have produced quite promising results. We were able to successfully carry out a word-level alignment of entire transcriptions spanning minutes or even a whole hour of audio with remarkably few serious alignment errors, especially when we could use existing manually aligned annotation units to constrain the automatic alignment, as is usually the case for most recent language documentation corpora. An evaluation on several manually aligned test sessions showed that the median time differences between constrained automatic versus manual alignment are comparable to median human interaligner time differences. Our evaluation studies on corpora of Hooc’ak and Texistepec Popoluca recordings also showed that even unconstrained automatic alignment can yield quite impressive alignment results for well-transcribed monological narratives, with median time differences close to those of constrained automatic alignment. This depends, however, on the nature of the transcribed recording and the quality of the transcription. Unconstrained automatic alignment is unable to deal with dialogical texts with many speaker overlaps and can be led astray by parts of the recording that are not transcribed. We have also made the more general observation that the quality of automatic alignment with WebMAUS depends much less on the quality of grapheme-to-phoneme conversion and acoustic models than on the quality and completeness of the transcription. Untranscribed parts of a recording such as filled pauses, backchannel responses, or conversely, transcribed words that do not actually occur in the audio signal will deteriorate the quality of automatic alignment. In the case of constrained forced alignment, we have also observed that smaller prealigned annotation units lead to a better alignment quality.

We believe that the possibility to automatically align transcriptions with audio/video data and to segment the latter into phones and words without the necessity of training acoustic models for individual languages, relying in-
Table 5: Time differences between unconstrained and constrained forced alignment with WebMAUS and a pre-existing manual word-level time alignment of a Hoocá 2 corpus (word start times only)

| Language | Texts | Words per AU | Words | Unconstrained Alignment | Constrained Alignment |
|----------|-------|--------------|-------|-------------------------|-----------------------|
|          | mean  | median | max   | mean  | median | max   | mean  | median | max   |
| Hoocá    | 41    | 8.14   | 12,287| 4,279 ms | 60 ms | 194,289 ms | 279 ms | 50 ms | 21,738 ms |

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5. Acknowledgements

6. References