

BFA: REAL-TIME MULTILINGUAL TEXT-TO-SPEECH FORCED ALIGNMENT

Abdul Rehman , Jingyao Cai, Jian-Jun Zhang, Xiaosong Yang

Faculty of Media, Science and Technology
Bournemouth University
Bournemouth, United Kingdom

ABSTRACT

We present Bournemouth Forced Aligner (BFA), a system that combines a Contextless Universal Phoneme Encoder (CUPE) with a connectionist temporal classification (CTC)-based decoder. BFA introduces explicit modelling of inter-phoneme gaps and silences and hierarchical decoding strategies, enabling fine-grained boundary prediction. Evaluations on TIMIT and Buckeye corpora show that BFA achieves competitive recall relative to Montreal Forced Aligner at relaxed tolerance levels, while predicting both onset and offset boundaries for richer temporal structure. BFA processes speech up to 240 \times faster than MFA, enabling faster than real-time alignment. This combination of speed and silence-aware alignment opens opportunities for interactive speech applications previously constrained by slow aligners.

Index Terms— alignment, text-to-speech, forced alignment, multilingual, phoneme boundary, speech recognition

1. INTRODUCTION

Accurate phoneme-level time alignment is important for speech processing pipelines, yet existing forced alignment tools are often language-specific and computationally expensive. Forced alignment—determining precise temporal boundaries for phonemes given known transcription—underpins applications from speech synthesis to audio-visual synchronization. Despite decades of research, current approaches face significant limitations constraining their applicability in modern pipelines.

The forced alignment landscape evolved significantly with Montreal Forced Aligner (MFA) [1], establishing parallel processing through Kaldi and becoming the dominant tool. Recent neural approaches include Charsiu [2] pioneering text-independent alignment using Wav2Vec2 models. WhisperX [3] demonstrated the integration of modern ASR

systems with forced alignment, achieving 12-fold transcription speedup through batched inference. However, comparative studies consistently show that traditional HMM-GMM approaches like MFA continue to outperform modern ASR-based methods in pure alignment tasks, with MFA achieving 41.6% word-level accuracy at 10ms tolerance on TIMIT compared to 22.4% for WhisperX [4]. The MAPS neural system [5] represents a notable exception, achieving 28% relative improvement over MFA through bidirectional LSTM architectures with interpolation techniques.

Research in universal phoneme representation has developed through IPA-based approaches, with systems employing 87-95 core phoneme sets [6, 7]. These developments parallel BFA’s classification system but focus on multilingual scenarios. Silent gaps have been largely overlooked in existing systems. Recent prosody-aware alignment work demonstrates that silence periods and prosodic boundaries significantly impact alignment quality [8].

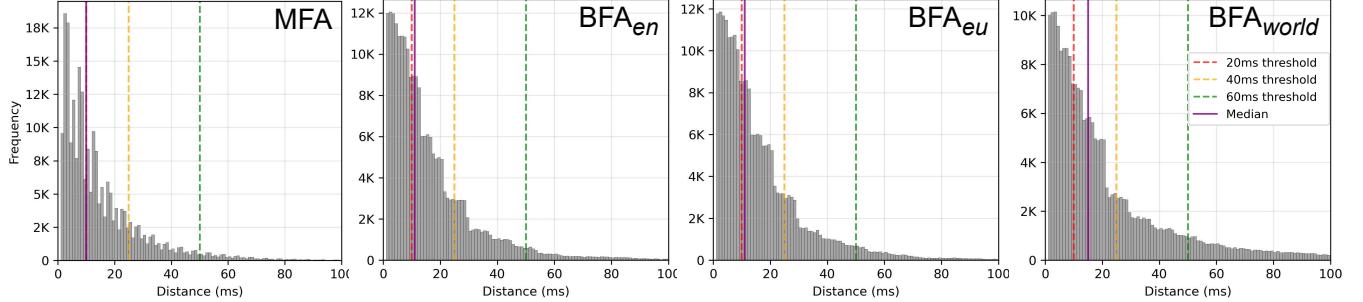
Current benchmarking on TIMIT and Buckeye corpora establishes performance baselines with MFA achieving 72.8% word-level accuracy at 20ms tolerance on TIMIT and 69.9% on Buckeye, while phone-level accuracy reaches 72.3% and 60.6% respectively at 20ms tolerance [4]. Traditional HMM-GMM approaches consistently outperform neural systems, with WhisperX achieving only 52.7% word-level accuracy at 20ms tolerance on TIMIT compared to MFA’s superior performance. While neural approaches show promise, the field faces a fundamental trade-off between computational complexity and accuracy, with enhanced CTC methods [9] achieving only 12-40% improvement in boundary errors despite significantly more complex training pipelines. The BFA system addresses these limitations through its combination of fast processing (0.2s for 10s audio, representing substantial speedup over MFA), universal phoneme representation, and punctuation-aware alignment that treats punctuation as structured silence periods.

2. METHODOLOGY

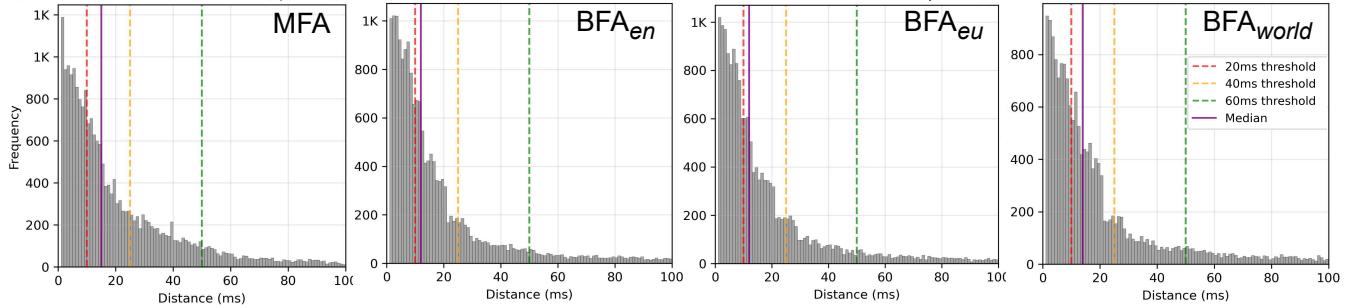
Our method integrates three key components: a contextless universal phoneme encoder for acoustic feature extraction, a multilingual phonemization module for text processing, and

Corresponding author: arehman@bournemouth.ac.uk

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(a) Error distances on **TIMIT** corpus using MFA, BFA_{en}, BFA_{eu}, and BFA_{world}



(b) Error distances on **Buckeye** corpus using MFA, BFA_{en}, BFA_{eu}, and BFA_{world}

Fig. 1. Histograms of error distances from ground truth phoneme boundaries to their nearest predicted boundaries.

a CTC-based dynamic programming decoder for temporal alignment. This architecture addresses the computational and linguistic limitations identified in contemporary forced alignment systems. The source code, pre-trained weights, and Python package are publicly available¹.

2.1. Contextless Phoneme Classification

We adapt the Contextless Universal Phoneme Encoder (CUPE) framework [10] for forced alignment through:

Table 1. Processing Speed and Real-time Performance

Dataset	Method	Time/Clip	Total Time
Buckeye (535s avg)	MFA	45 min	7 days
	BFA	60 s	1 hour
TIMIT (3.1s avg)	MFA	1 min	4.2 days
	BFA	0.25s	25 min
Speed Improvement Real-time Factor		45-240x	72-242x
		MFA: 52-194x, BFA: 0.05-0.1x	

Multi-task Learning Architecture: We implement dual classification objectives with separate prediction heads for 67-class phonemes and 17-class phoneme groups, including blank tokens for CTC training. This design enables hierarchical alignment at both fine-grained phoneme and coarse-grained phoneme group levels.

Training Data Selection: We train on full-sentence corpora rather than isolated words, using LibriSpeech [11] for English optimization and Multilingual LibriSpeech [12] for European coverage. Improved acoustic quality enables better phoneme discrimination.

Multilingual Model Variants: We develop three configurations: English-optimized (LibriSpeech), European multilingual (MLS across 7 languages excluding English), and universal (MSWC [13] covering 35 languages excluding English).

2.2. Multilingual Phoneme Mapping

We employ espeak-ng for text-to-phoneme conversion, mapping International Phonetic Alphabet symbols to our data-driven phoneme mapping system. We derive phonemes from frequency analysis of multilingual speech data, optimized for Indo-European languages in our training corpora. This reduces dependence on language-specific pronunciation dictionaries while maintaining phonetic precision. The phoneme selection can adapt to different language families by adjusting vocabulary based on target characteristics. We generate broader phoneme groups enabling coarse-grained alignment when needed.

¹www.github.com/tabahi/bournemouth-forced-aligner

2.3. Temporal Alignment Algorithm

We formulate the alignment problem using Connectionist Temporal Classification principles adapted for forced alignment scenarios. Given a target phoneme sequence of length S , we construct a CTC state path incorporating explicit blank states:

$$\text{path} = [\text{blank}, p_1, \text{blank}, p_2, \dots, \text{blank}, p_S, \text{blank}] \quad (1)$$

The alternating blank-phoneme structure enables modeling of variable-duration phonemes while maintaining monotonic alignment constraints. We employ dynamic programming with log-probability observations:

$$\alpha_t(s) = \max \begin{cases} \alpha_{t-1}(s) + \log P(o_t|s) & (\text{duration extension}) \\ \alpha_{t-1}(s-1) + \log P(o_t|s) & (\text{state transition}) \\ \alpha_{t-1}(s-2) + \log P(o_t|s) & (\text{blank skip}) \end{cases} \quad (2)$$

where blank skip transitions are constrained to prevent illegal consecutive identical phoneme transitions.

2.4. Alignment Optimization Strategies

We implement several algorithmic strategies to address limitations in standard CTC decoding for forced alignment applications:

Probability Calibration: We apply logarithmic probability boosting to expected phonemes using factor $\beta = 5.0$, addressing systematic underrepresentation in cross-lingual scenarios and improving target phoneme detection in challenging acoustic conditions.

Probability Floor Enforcement: We establish minimum probability thresholds $\epsilon = 10^{-8}$ for all target phonemes to prevent complete elimination during the alignment process, ensuring robust performance across diverse acoustic conditions.

Hierarchical Decoding: For utterances containing detected silence segments, we implement a divide-and-conquer approach by decomposing the alignment problem into independent sub-problems, applying separate Viterbi decoding to each continuous speech region.

Completeness Guarantee: We develop post-processing mechanisms that ensure 100% target phoneme coverage by identifying missing phonemes and inserting them at acoustically optimal frame positions based on maximum probability criteria.

Interval Boundary Prediction: We extend conventional onset-only prediction to estimate both phoneme start and end boundaries. The predicted end boundaries often occur before the subsequent phoneme onset, creating explicit inter-phoneme gaps that capture natural pause patterns in speech. However, the tolerance to gaps is an adjustable parameter

since some applications may require more context between phonemes.

3. EXPERIMENTS AND RESULTS

We evaluate on two benchmarks representing different conditions. TIMIT provides 6300 clean read utterances (3.1s average), while Buckeye offers spontaneous conversational speech from 40 speakers (535s average). We compare against Montreal Forced Aligner using standard metrics: recall at multiple tolerance levels (20ms, 40ms, 60ms), precision, and boundary distance accuracy.

Our evaluation examines three model configurations to investigate language-specificity trade-offs:

- English-optimized: Maximum performance on English speech denoted as BFA_{en}
- European multilingual: Cross-lingual performance across 8 European languages denoted as BFA_{eu}
- Universal: Broad language coverage across 35 diverse languages denoted as BFA_{world}

Table 2 presents alignment performance across both evaluation datasets on English speech. Our approach demonstrates competitive recall performance, particularly at relaxed tolerance levels that reflect practical application requirements. Our dual boundary prediction results in 30-40% of phonemes having preceding inter-phoneme gaps on these datasets, compared to conventional aligners that model no gaps between consecutive phonemes.

Table 1 presents computational performance comparison, demonstrating substantial efficiency improvements that enable real-time processing capabilities.

4. DISCUSSION

Our investigation demonstrates several contributions addressing fundamental limitations in current approaches.

Cross-lingual Performance: The BFA_{eu} and BFA_{world} models, trained without English data, achieve performance on par with MFA and BFA_{en} on English test sets. This suggests that the universal phoneme representation can generalize across languages, though evaluation on additional languages would further validate this approach.

End Boundary: By predicting phoneme end boundaries that often occur before the next phoneme onset, our approach explicitly models inter-phoneme gaps that conventional aligners ignore entirely. While this results in approximately twice the boundary predictions and consequently lower precision scores (since the annotations are also onset-only), it provides a more complete representation of speech temporal structure where 30-40% of phonemes exhibit small inter-phoneme gaps as shown in Table 3.

Table 2. Alignment Performance and Boundary Detection Statistics. *Precision at 20ms tolerance is calculated considering only onset boundaries to align with conventional metrics.

Method	Dataset	Recall (%)			Precision (%)			Totals		Errors (%)		
		20ms	40ms	60ms	20ms*	20ms	40ms	60ms	Annotated	Predicted	Deletions	Insertions
MFA	TIMIT	71.9	81.2	82.8	81.2	81.2	96.2	98.9	234,127	210,828	3.49	1.11
BFA _{en}	TIMIT	71.4	84.6	87.9	82.3	55.6	84.7	95.3	234,841	402,962	3.04	4.66
BFA _{eu}	TIMIT	71.0	84.7	88.1	80.9	55.2	83.8	94.6	234,841	402,982	2.76	5.37
BFA _{world}	TIMIT	60.9	73.2	77.4	77.5	50.9	79.9	91.7	234,841	376,962	10.86	8.31
MFA	Buckeye	58.1	70.8	74.8	58.5	58.5	79.5	88.6	24,135	25,036	15.37	11.37
BFA _{en}	Buckeye	63.7	73.2	76.3	61.4	48.6	75.8	86.6	20,905	40,984	18.83	13.38
BFA _{eu}	Buckeye	60.5	70.6	73.5	59.8	47.9	74.9	85.6	20,905	40,134	21.87	14.43
BFA _{world}	Buckeye	58.6	67.7	71.0	54.1	44.8	71.4	82.6	20,905	39,208	23.34	17.40

Table 3. Boundary Distance and Inter-phoneme Gap Analysis

Method	Dataset	Known to Aligned (ms)		Aligned to Known (ms)		Inter-phoneme Gap Statistics		
		Mean	Median	Mean	Median	Median (ms)	Std (ms)	%gap/phone
MFA	TIMIT	13.2	9.5	11.8	8.6	60.0	97.3	1.54%
BFA _{en}	TIMIT	14.1	10.7	20.0	17.2	40.0	51.2	35.30%
BFA _{eu}	TIMIT	14.4	11.0	20.1	17.2	41.0	50.6	34.79%
BFA _{world}	TIMIT	16.4	12.5	21.0	18.4	41.0	83.0	33.25%
MFA	Buckeye	16.8	13.8	17.9	14.9	300.0	530.2	4.81%
BFA _{en}	Buckeye	13.6	9.7	20.9	18.3	39.0	468.2	31.91%
BFA _{eu}	Buckeye	13.7	9.7	20.9	18.3	40.0	385.7	31.66%
BFA _{world}	Buckeye	14.4	10.6	21.4	18.9	39.0	391.2	34.04%

Table 4. Ablation Study: Impact of Algorithm Parameters on TIMIT

Model	Mode	Precision (%)		Recall (%)	
		20ms	60ms	20ms	60ms
BFA _{en}	Default	55.6	95.3	71.4	87.9
BFA _{en}	No enforce	55.6	95.3	71.4	87.9
BFA _{en}	No boost	56.2	95.5	73.5	87.1
BFA _{eu}	Default	55.2	94.6	71.0	88.1
BFA _{eu}	No enforce	55.2	94.6	71.0	88.1
BFA _{eu}	No boost	55.8	95.0	71.2	85.5
BFA _{world}	Default	50.9	91.7	60.9	77.4
BFA _{world}	No enforce	51.0	92.1	58.1	74.2
BFA _{world}	No boost	51.2	92.0	35.4	49.0

Ablations: The two ablations presented in Table 4 highlight the importance of our algorithmic contributions. Probability boosting does not affect the performance of the English-only model but helps the universal model where the diverse phoneme set can be biased towards language-specific phonemes. The 100% target coverage enforcement slightly improves the performance of the universal model given its lower baseline recall rate. The ablations also show that these optimizations do not compromise boundary distance accuracy, indicating that they effectively enhance phoneme detection without sacrificing temporal precision.

We presented a forced alignment approach addressing limitations in phoneme-level temporal boundary detection. Combining universal phoneme representation with contextless processing and explicit prosodic modeling achieves substantial computational improvements while maintaining competitive accuracy. Evaluation on TIMIT and Buckeye shows competitive recall performance versus established baselines with acceptable boundary distance accuracy. The approach shows promising results across different training configurations, from English-optimized to models trained on non-English data that generalize to English evaluation.

The computational efficiency improvements enable real-time processing scenarios, expanding forced alignment applications to interactive and streaming contexts. Future research directions include investigating the approach’s effectiveness on tonal languages, exploring applications in multilingual speech processing pipelines, and examining the potential for adaptive boundary prediction strategies that optimize precision-completeness trade-offs based on application requirements.

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