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# Speech Segmentation using Regression Fusion of Boundary Predictions

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## Abstract

In the present work we study the appropriateness of a number of linear and non-linear regression methods employed on the task of combining multiple phonetic boundary predictions. The proposed fusion schemes are independent of the implementation of the individual segmentation engines as well as from their number. In order to illustrate the practical significance of the proposed approach, we employ 112 speech segmentation engines based on hidden Markov models (HMMs). These engines differ in the setup of the HMMs as well as in the speech parameterization techniques they employ. In the experimental evaluation we firstly evaluate the performance of various recent speech features, which have not been tested on the speech segmentation task yet. Secondly, we evaluate the performance of several new fusion schemes for phonetic boundary predictions and finally we contrast them to some recently reported methods. Throughout this comparison, on the established for the phonetic segmentation task TIMIT database, we demonstrate that the support vector regression scheme is capable of achieving more accurate predictions, when compared to other fusion schemes reported so far.

**Keywords:** speech segmentation, regression fusion, hidden Markov models

## 1. Introduction

The contemporary speech technology heavily depends on large speech corpora, whose annotation is a tedious task and is usually performed manually or semi-automatically. In general, speech databases consist of recordings and some sort of indexing, which can include word transcription, phonetic transcription, phone level time-alignment and prosodic annotation (Sagisaka et al., 1997; Campbell and Black, 1997; Iwano et al., 2004). While in automatic speech recognition (ASR) word and phonetic transcriptions are sufficient for the training of acoustic models, in text to speech (TTS) synthesis phone-level time-alignment is also needed (Dutoit, 1997). Furthermore, when bootstrap data with time-alignment are available the HMM parameters are better initialized and fine-tuned (Malfrere et al., 2003). In general, word transcriptions are extracted easily from the speech waveform by utilizing automatic transcribers and manual corrections over the automatically extracted word sequence. Similarly easy, phonetic transcription is usually extracted from the word level annotation using grapheme to phoneme converters. In contrast to the above indexes, the extraction of phonetic time-alignment is considered as a difficult task.

Presently, the most accurate way to extract the time boundaries of the phones of a speech waveform is manually. However, manual segmentation is a tedious, time-consuming and costly task that can be performed only by expert phoneticians (Acero, 1995). Moreover, the use of human annotators introduces subjectivity in the position of the phone transitions (van Hemert, 1991; Pellom and Hansen, 1998). Due to the difficulties that manual segmentation presents, methods have been developed for the automatic segmentation of speech waveforms to the corresponding phonetic units. Automatic segmentation techniques can roughly be divided into two major categories, implicit and explicit segmentation (van Hemert, 1991). In the explicit case, the segmentation algorithm is linguistically constrained to an a priori known phonetic sequence, while in the implicit case there is no prior knowledge of the corresponding phonetic sequence. Explicit segmentation methods are utilized when indexing database recordings, where the phonetic sequence is usually known.

Various approaches have been proposed for the task of speech segmentation, such as: the detection of variations/similarities in spectral (Svendsen and Soong, 1987; Dalsgaard et al., 1991; van Hemert, 1991; Grayden and Scordilis, 1994; Petek et al., 1996; Aversano et al., 2001) or prosodic (Adami and Hermansky, 2003) parameters of speech, the template matching using dynamic programming and/or the synthetic speech (Bajwa et al., 1996; Paulo and Oliveira, 2003; Malfrere et al., 2003) and the discriminative learning segmentation (Keshet et al., 2007).

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1 The most frequently used speech segmentation approach is based on HMM phone models (Ljolje  
2 and Riley, 1991; Brugnara et al., 1993; Ljolje et al., 1997; Pellom and Hansen, 1998; Mporas et al.,  
3 2008). This method became popular as it is less prone to gross errors (Kominék et al., 2003) and  
4 because of its well-known structure from the area of speech recognition. In Figure 1, we show the  
5 block diagram of the HMM-based segmentation approach for the linguistically constrained case. In this  
6 method each speech waveform is initially decomposed to a sequence of feature vectors, using a speech  
7 parameterization technique. Afterwards, an HMM phone recognizer is utilized to force-align the feature  
8 vector sequence against the corresponding phonetic sequence through the Viterbi algorithm (Viterbi,  
9 1967). The outcome of this process is the time positions of the phonetic transitions.

10  
11  
12 *Figure 1*

13  
14  
15 There are two main training strategies of the HMM phone models, depending on the availability of  
16 manually segmented speech data (bootstrap data). When bootstrap data are available, isolated-unit  
17 training is performed, where the speech frames that correspond to each phone are separately used to  
18 initialize and refine the HMM parameters of the corresponding phone model. During initialization the  
19 data are uniformly segmented and associated to the corresponding sequence of HMM states. The  
20 refinement of the HMM parameters is performed through the Viterbi and Baum-Welch (Baum et al.,  
21 1970) algorithms. When bootstrap data are not available, embedded training is performed, where the  
22 HMM parameters of all models are computed simultaneously utilizing all the speech frames of the  
23 training data. In embedded training the models are initialized by setting global values to the HMM  
24 parameters of all phone models (flat initialization) and refined by Baum-Welch algorithm. Phone  
25 models can be trained on other speech corpora and further be used with/without adaptation on the target  
26 data.

27 HMM-based segmentation has successfully been combined with post-processing techniques to  
28 refine the predicted phone boundaries (Sethy and Narayanan, 2002; Kim and Conkie, 2002; Toledano  
29 et al., 2003; Matousek et al. 2003; Wang et al., 2004; Adell et al., 2005; Lee, 2006; Lin and Jang, 2007;  
30 Lo and Wang, 2007). Furthermore, methods for fusion of the segmentation outputs from different  
31 approaches and/or systems have been proposed. In (Jarifi et al., 2008) it has been shown that linear  
32 combination of the predictions of global and local approaches for automatic segmentation improves the  
33 segmentation accuracy. In (Park and Kim, 2006; Park and Kim, 2007) the overall segmentation  
34 accuracy is improved using a linear combination of the predictions of several independent HMM-based  
35 segmentation methods and a gradient projection method for the computation of the weights. (Kominék  
36 and Black, 2004) showed that big segmentation mistakes have a greater impact on the perceived quality  
37 of an utterance than several smaller ones, and therefore averaging among a number of estimates for  
38 each boundary is a simple and effective way to avoid gross inaccuracies.

39 Up to the authors' best knowledge, all previous studies on fusion of a number of segmentation  
40 engines (Kominék and Black, 2004; Park and Kim, 2006; Park and Kim, 2007; Jarifi et al., 2008) can  
41 be generalized to some form of linear combination of the boundary positions that were predicted from  
42 several independent segmentation engines. Moreover, these studies considered segmentation of speech  
43 waveforms only for the case of single-speaker recordings.

44 Here, we propose the use of regression analysis for the fusion of the predictions of independent  
45 segmentation engines. Specifically, we evaluate both linear and non-linear regression algorithms that  
46 have been successfully used on different numerical prediction tasks, such as forecasting and phone  
47 duration prediction.

48 In contrast to the previous studies on fusion of segmentation engines, in the present work we  
49 consider the general case of speaker-independent phonetic segmentation and thus perform validation  
50 experiments on the well-known TIMIT multi-speaker database (Garofolo, 1988), which has been  
51 established for the validation of phonetic segmentation approaches (Ljolje and Riley, 1991; Brugnara et  
52 al., 1993; Grayden and Scordilis, 1994; Wightman and Talkin, 1997; Pellom and Hansen, 1998;  
53 Aversano et al., 2001; Keshet et al., 2007; Lo and Wang, 2007; Mporas et al. 2008). In order to  
54 increase the variability among the segmentation engines' predictions we utilized seven different  
55 parameterization techniques that have successfully been used on the speech recognition task. It should  
56 be noted that five out of the seven speech parameterizations considered here have not been studied on  
57 the speech segmentation task before, and as reported in Section 4 some of them offer an advantageous  
58 performance when compared to the widely-used Mel frequency cepstral coefficients (MFCCs).

59 The proposed fusion scheme is independent from the implementation of the individual  
60 segmentation engines as well as from their number. We assume that the output of any given regression

1 algorithm, i.e. the predicted phonetic boundary positions, will be more precise than (or at least as good  
 2 as) the ones predicted by each of the individual segmentation engines. This is because the regression  
 3 algorithms are capable of capturing and modelling the systematic errors of each segmentation engine,  
 4 as well as the systematic boundary shifts among the segmentation engines across each boundary type.  
 5 By the term *boundary type* we refer to the transition between the left context phonetic class of a  
 6 boundary to the right context class, e.g. vowels, affricates, fricatives, nasals, glides, stops and silence.  
 7 In the experimental comparison presented in Section 4, we demonstrate that the support vector  
 8 regression scheme is capable of achieving more accurate predictions, when compared to various  
 9 implementations of linear fusion schemes reported in the literature.

10 Since in the present work we do not examine the recognition of the phonetic sequence but the  
 11 accurate detection of the phonetic transition positions in what follows explicit segmentation is assumed.

12 The remaining of this article is organized as follows: In Section 2 we describe the general  
 13 regression fusion structure for combining multiple phonetic boundary predictions, as well as the  
 14 regression algorithms evaluated here. In Section 3 we explain the experimental setup and outline the  
 15 baseline segmentation engines utilized in the experiments. Next, in Section 4 we report results related  
 16 to the performance of various recent and traditional speech features, as well as to the ranking of a  
 17 variety of fusion schemes for phonetic boundary predictions. Finally, in Section 5 we conclude this  
 18 work.

## 20 **2. Regression Fusion of Multiple Phonetic Boundary Predictions**

21  
 22 The block diagram of the proposed regression fusion scheme for combining multiple different  
 23 segmentation engines is presented in Figure 2. This general fusion scheme covers both the linear and  
 24 non-linear fusion cases and is independent from the implementation of the individual segmentation  
 25 engines as well as from their number.

26  
 27  
 28 **Figure 2**

29  
 30  
 31 Let us define a set of  $N$  phone transition position predictions  $S_i$ , with  $1 \leq i \leq N$ , as the outcome of  
 32  $N$  different segmentation engines. These engines, which in the rest of this paper will be referred to as  
 33 baseline segmentation engines (BSEs), produce phonetic boundary predictions that are independent to  
 34 each other. The predictions are combined with the use of a regression fusion function  $f$  to create a  
 35 new phone transition position prediction  $S_{pred} = f(S_1, S_2, \dots, S_N, p(b))$ , where  $p(b)$  defines the parameters  
 36 of the fusion function, and  $b$  defines the phonetic boundary type. The parameters of the fusion  
 37 function,  $p(b)$ , are adjusted by minimizing an error function  $\epsilon_f(S_{real}, S_{pred})$ , which is specific for each  
 38 fusion function and expresses the misalignment between the real and predicted phone transition  
 39 positions on a training bootstrap set  $D(b)$ , i.e.  $\arg \min_{D(b), p(b)}(\epsilon_f)$ . For the real phone transition positions,  $S_{real}$ ,

40 we consider the manually annotated labels of the phonetic boundaries available in the speech database.

41 Since different BSEs offer different performance at specific boundary types (Jarifi et al., 2008), we  
 42 hypothesize that an appropriate combination of them could increase the overall performance.  
 43 Furthermore, intuitively we assume that specific boundary fusion techniques would be more successful  
 44 on the given task than other techniques. For that purpose we are interested in investigating the  
 45 performance of various fusion functions and evaluating their applicability for the present problem.  
 46 Specifically, we consider fusion approaches that have already been studied in the literature such as the  
 47 simple average (Kominek and Black, 2004), the best-only selection (Park and Kim, 2006), the linear  
 48 combination of (Jarifi et al., 2008) but more importantly the linear regression, multilayer perceptron  
 49 neural networks, support vector regression and model trees, whose performance haven't been  
 50 investigated on the specific task, yet.

51 For the purpose of comprehensiveness in the following subsections we review the regression  
 52 techniques of interest.

### 53 **2.1. Linear Regression: LR(AIC)**

54  
 55 In linear regression (LR) all boundary predictions are weighted and summed, i.e. the fusion  
 56 function  $f$  takes the form  
 57

$$S_{pred} = w_0(b) + \sum_{i=1}^N w_i(b) S_i. \quad (1)$$

The attribute weights  $w_i(b)$ , for each boundary type  $b$ , are computed by applying the least-squares criterion over the training data,

$$\arg \min_{w_i(b)} \left\{ \sum_{i=1}^{D(b)} \left( S_{real}(i) - w_0(b) - \sum_{j=1}^N w_j(b) S_j(i) \right)^2 \right\}, \quad (2)$$

where  $S_j(i)$  is the position prediction of the  $j$ -th BSE for the  $i$ -th boundary,  $D(b)$  is the size of the training data for the corresponding boundary type and  $w_0(b)$  stands for the bias.

In the case of *average fusion* the weights are  $w_i(b) = 1/N$ , for  $1 \leq i \leq N$ . As for the *best prediction selection* case for boundary type  $b$ , the weights are  $w_i(b) = 1$ , for  $i = best$  and  $w_i(b) = 0$ , for  $i \neq best$ .

Instead of using all attributes, M5' decision trees (refer to Section 2.4) can be applied for feature selection (Wang and Witten, 1997). During feature selection the attribute with the smallest standardized coefficient is iteratively removed until no improvement is observed in the error estimation. The error estimation is given by the Akaike information criterion (Akaike, 1974) as:

$$AIC = 2k + D(b) \left( \ln \left( \frac{2\pi R_S}{D(b)} \right) + 1 \right), \quad (3)$$

where  $k$  is the number of parameters in the statistic model and  $R_S$  is the residual sum of squares:

$$R_S = \sum_{i=1}^{D(b)} (S_{real} - S_{pred})^2. \quad (4)$$

Here  $R_S$  indicates the cumulative squared error with respect to the real boundaries, and a smaller value of the AIC indicates for a better model.

## 2.2. Multilayer Perceptron Neural Networks: MLP NN

Neural networks (NNs) with three layers have been proved capable for numerical predictions (Chester, 1990), since neurons are isolated and region approximations can be adjusted independently to each other. In detail, the output  $z_j$  of the  $j$ th neuron in the hidden layer of a multilayer perceptron (MLP) NN is defined as:

$$z_j = f \left( \sum_{i=1}^N w_{ji}^{(1)}(b) S_i + w_{j0}^{(1)}(b) \right), \quad j = 1, 2, \dots, M, \quad (5)$$

where  $f(x) = (1 + e^{-x})^{-1}$  is the sigmoid activation function,  $M$  is the total number of neurons in the hidden layer, and  $w_{ji}^{(1)}(b)$  and  $w_{j0}^{(1)}(b)$  are the weight and bias terms, respectively. In the present work the output layer of the MLP NN consists of a single unthresholded linear unit, and the network output,  $S_{pred}$ , is defined as:

$$S_{pred} = \sum_{j=1}^M w_j^{(2)}(b) z_j + w_0^{(2)}(b). \quad (6)$$

All weights are adjusted during the training through the back propagation algorithm.

## 2.3. Support Vector Regression: SVR

For the non-linear case of support vector regression (SVR) the two most widely used algorithms are the  $\varepsilon$ -SVR (Vapnik, 1998) and the  $\nu$ -SVR (Scholkopf et al., 2000). Here we utilize the  $\nu$ -SVR because of its ability to automatically adjust the  $\varepsilon$  insensitive cost parameter. Given the set of training data  $\{\mathbf{x}_i, S_{real}(i)\}$  for the boundary type  $b$ , with  $\mathbf{x}_i = [S_1(i), \dots, S_N(i)]^T$  and  $1 \leq i \leq D(b)$ , a function  $\phi$  maps the attributes to a higher dimensional space. The primal problem of  $\nu$ -SVR,

$$\arg \min_{\mathbf{w}, \varepsilon, \xi_i, \xi_i^*} \left\{ \frac{1}{2} \mathbf{w}^T \mathbf{w} + C \left( \nu \varepsilon + \frac{1}{k} \sum_{i=1}^k (\xi_i + \xi_i^*) \right) \right\}, \quad (7)$$

is subject to the following restrictions:  $(\mathbf{w}^T \phi(x_i) + \beta) - S_{real}(i) \leq \varepsilon + \xi_i$ ,  $S_{real}(i) - (\mathbf{w}^T \phi(x_i) + \beta) \leq \varepsilon + \xi_i^*$ ,  $\xi_i, \xi_i^* \geq 0$ , with  $\mathbf{w} \in \mathbb{R}^N$ ,  $\beta \in \mathbb{R}$ ,  $i \in [0, N]$  and  $\varepsilon \geq 0$ . Here,  $\xi_i$  and  $\xi_i^*$  are the slack variables for exceeding the target value more or less than  $\varepsilon$ , respectively, and  $C$  is the penalty parameter. The kernel function is  $K(\cdot, \cdot) = \phi(x)^T \phi(x)$ . The value of  $\nu$  affects the number of support vectors and training errors.

Here we consider the radial basis kernel function  $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$ .

## 2.4. Model Trees: M5'

Here we consider the M5' model tree algorithm proposed by (Wang and Witten, 1997), which is a rational reconstruction of M5 method developed by (Quinlan, 1992). In tree structures, leaves represent classifications and branches represent conjunctions of attributes. The M5' tree is a binary decision tree constructed in two steps, namely the splitting and the pruning phase. During splitting, for each node the algorithm computes the best attribute to split the  $T$  subset of data that reaches the node. The error criterion is the standard deviation of each class value that reaches each node. The attribute  $i$  with the maximum standard deviation reduction  $\hat{\sigma}$  is selected for splitting that node, i.e.

$$\arg \max_i \left\{ \hat{\sigma} = \sigma(T) - \sum_j \frac{|T_{ij}|}{|T|} \times \sigma(T_{ij}) \right\} \quad (8)$$

where  $T_{ij}$  are the subsets that result from splitting the node according to the chosen attribute  $i$ , with  $1 \leq i \leq N$ . The splitting process, which results to child nodes with smaller standard deviation, terminates when class values of the instances that reach a node have standard deviation equal to a small fraction of the original instance set, or if only few instances remain. When splitting is completed a large tree structure will be constructed. For each node one linear regression model is calculated and simplified by dropping the attributes that reduce the expected error. The error for each node is the averaged difference between the predicted and the actual value of each instance of the training set that reaches the node. The computed error is weighted by the factor  $(n+\nu)/(n-\nu)$ , where  $n$  is the number of instances that reach that node and  $\nu$  is the number of parameters in the linear model that give the class value at that node. This process is repeated until all the examples are covered by one or more rules. During the pruning phase, sub-trees are pruned if the estimated error for the linear model at the root of a sub-tree is smaller or equal to the expected error for the sub-tree.

## 3. Experimental Setup

The regression fusion scheme, shown in Figure 2, employs multiple phonetic boundary position predictions that are obtained from independent segmentation engines (refer to Section 2). In the present work these BSEs were implemented as HMM-based segmentation engines, utilizing the HTK toolkit (Young et al., 2006), and differ in the speech parameters fed on their input and/or in the settings of the HMM engine itself. Several factors such as the number of HMM states, the number of Gaussian mixtures per state, the frame shift and length, and the context dependency of the phone models can affect the segmentation performance. Although each combination of these factors would result to a different BSE, here we restrict the evaluation to 112 different BSEs. Their settings were chosen based on practical considerations and findings of previous research on speech segmentation (Brugnara et al., 1993; Pellom and Hansen, 1998; Park and Kim, 2006; Park and Kim, 2007).

Specifically, an experimental setup similar to (Brugnara et al., 1993) was followed here. In particular, each BSE utilized 3-state and 4-state left-to-right HMMs, without skipping transitions to train one model for each phone. Both context-independent (CI) and context-dependent (CD) HMM models were trained. Every HMM state was modelled by 1, 2, 4 and 6 linear combinations of continuous Gaussian densities with diagonal covariance matrix. For the case of CD phone models, similar HMM states were tied, with outlier threshold (parameter RO in HTK) equal to 100 and cluster log-likelihood threshold (parameter TB in HTK) equal to 350. In both CI and CD cases, speaker-independent models were trained.

### 3.1 Speech Pre-processing and Speech Parameterization

It has been shown in the literature (Pauws et al., 1996; Paulo and Oliveira, 2003) that some speech features present significantly better ability to detect certain types of phonetic transitions compared to others. Since different speech parameterization techniques lead to somehow different boundary position predictions, which for specific transitions are more accurate than others, we hypothesized that if such

1 predictions are combined in a reasonable manner the outcome of their fusion might turn out to be  
 2 beneficial in terms of accuracy. Based on this assumption and on the idea of performing fusion per  
 3 boundary type, in the present work we implemented seven speech parameterization techniques, which  
 4 feed multiple parallel BSEs, whose outputs are combined (Figure 2).

5 In brief, the seven speech parameterizations implemented here utilize the standardized speech  
 6 processing procedure (ETSI, 2000; ETSI, 2007). In that way, a number of setup dependent parameters  
 7 (e.g. sampling frequency, frequency bandwidth of speech signal, etc) that were disparate in the original  
 8 studies, where these speech parameterizations were proposed initially, were unified. Specifically,  
 9 assuming speech signal sampled at 16 kHz, we adapted all speech parameterization techniques to  
 10 frequency bandwidth [100, 7000] Hz. Moreover, according to the ETSI procedures, uniform pre-  
 11 processing, consisting of pre-emphasis with factor  $a=0.97$ , frame blocking and windowing of the  
 12 speech signal were carried out. Speech waveforms were frame blocked every 5 milliseconds as in  
 13 (Brugnara et al., 1993; Pellom and Hansen, 1998; Jarifi et al., 2008; Park and Kim, 2007), using a 16  
 14 millisecond window. Here we do not make use of the 20 millisecond window length as in (Brugnara et  
 15 al., 1993) due to the restriction of the discrete wavelet packet transform (DWPT), on which all wavelet-  
 16 based features rely on, to be applied on a number of samples which is a power of two.

17 After the pre-processing of the speech signal, the feature extraction was performed following the  
 18 particular speech parameterization procedure, as it was introduced by the original authors, except that  
 19 we adapted the frequency range of all filter-banks to the desired bandwidth. In the following  
 20 paragraphs we summarize these changes:

21 **Mel-Frequency Cepstral Coefficients (MFCC):** The MFCC implementation of (Slaney, 1998) utilized  
 22 a filter-bank of forty equal-area filters, which covers the frequency range [133, 6855] Hz. The first 13  
 23 filters in the filter-bank are with linearly spaced centre frequencies in the range [200, 1000] Hz, and the  
 24 next 27 have their centres logarithmically spaced in the range [1071, 6400] Hz, with logarithmic factor  
 25 1.0711703.

26 **Linear Frequency Cepstral Coefficients (LFCC):** The LFCC parameterization as in (Davis and  
 27 Mermelstein, 1980) was adapted by implementing a filter-bank of forty equal-width equal-height  
 28 filters, each one with pass-band of 164 Hz. This resulted in filter-bank that covers the frequency range  
 29 [133, 6857] Hz.

30 **Human Factor Cepstral Coefficients (HFCC-E):** The HFCC filter-bank of (Skowronski and Harris,  
 31 2004) that has twenty-nine filters covering bandwidth [0, 6250] Hz, was adapted by discarding the two  
 32 filters with lowest centre frequencies and adding a new one at the high-frequency end of the filter-bank.  
 33 This resulted in a filter-bank that covers the frequency range [125, 6844] Hz with twenty-eight filters.  
 34 The filter-bank was designed for E-factor equal to one.

35 **Perceptual Linear Prediction (PLP):** The eighteen-filter Bark-spaced filter-bank utilized in the PLP  
 36 (Hermansky, 1990) covering the frequency range [0, 5000] Hz was adapted by discarding the lowest-  
 37 frequency filter and adding two new high-frequency filters with Bark-spacing. This led to a filter-bank  
 38 of nineteen filters that cover the frequency range [100, 6400] Hz, which is the closest feasible  
 39 implementation.

40 **Wavelet-Packet Features (WPF):** In the WPF (Farooq and Datta, 2001) the twenty-four frequency  
 41 subbands approximating the Mel-scale in the frequency range [0, 8000] Hz were reduced to twenty-two  
 42 by eliminating the lowest and highest frequency subbands. This way the frequency range [125, 7000]  
 43 Hz is covered. The WPF utilize wavelet packet decomposition (WPD) based on the Daubechies  
 44 wavelet of order 12.

45 **Subband-Based Cepstral parameters (SBC):** In the SBC (Sarikaya and Hansen, 2000) the authors used  
 46 twenty-four Mel-spaced subbands to cover the frequency range [0, 4000] Hz. We adjusted this  
 47 frequency division to the desired frequency range by discarding the two lowest subbands and adding at  
 48 the high-frequency end six new subbands of 500 Hz each. This resulted in Mel-scale frequency  
 49 warping with twenty-eight subbands that cover the frequency range [125, 7000] Hz. The SBC utilize  
 50 WPD based on the Daubechies wavelet of order 32.

51 **Mixed Wavelet Packet Advanced Combinational Encoder (MWP-ACE):** The MWP-ACE speech  
 52 features (Nogueira et al., 2006) utilize twenty frequency subbands to cover the frequency range [0,  
 53 8000] Hz. In our implementation, we discarded the lowest and highest subbands, which resulted in a  
 54 total of eighteen subbands that cover the frequency range [125, 7000] Hz. The MWP-ACE features  
 55 utilize WPD based on the Symlets family with the Symlets wavelet of order 6 on the first level,  
 56 Symlets 5 on the second, etc.



1 A comprehensive description of the different speech parameterizations utilized here can be found  
 2 in the corresponding references. In all speech parameterization schemes we computed only the first  
 3 thirteen cepstral coefficients. Before training the HMM models, feature vectors composed of the static  
 4 speech features and their delta coefficients were composed, resulting to a 26 dimensional parametric  
 5 vector.

### 6 7 **3.2 Fusion Scheme**

8  
9 We utilized the Weka (Witten and Frank, 2005) and LibSVM (Chang and Lin, 2002)  
 10 implementations of the regression algorithms described in Section 2. The MLP consisted of a three-  
 11 layer neural network. The number of input nodes was equal to the number of BSEs while the number of  
 12 hidden nodes was empirically set equal to 65. The output layer of the MLP NN contains a single  
 13 neuron. In the case of SVR, the  $\nu$  parameter was empirically set to 0.5, while the  $C$  and  $\gamma$  parameters,  
 14 which were set equal to  $2^l$  and  $2^g$  respectively, were determined by grid search ( $C=\{2^{-5}, 2^{-2}, \dots, 2^4\}$ ,  
 15  $\gamma=\{2^{-15}, 2^{-12}, \dots, 2^3\}$ ) on a randomly selected bootstrap subset, consisting of approximately 1/4 of the  
 16 training data.

### 17 18 **3.3 Evaluation Database**

19  
20 The performance of each regression algorithm was evaluated on TIMIT database (Garofolo, 1988).  
 21 TIMIT is the most widely used corpus for phone segmentation and has been established for this task  
 22 (Brugnara et al., 1993; Wightman and Talkin, 1997; Keshet et al., 2007). Briefly, it consists of  
 23 microphone quality recordings of 630 American-English speakers (10 sentences per speaker), with  
 24 sampling frequency 16 kHz and resolution 16-bit.

25 Here, we rely on the standard train/test subset division of the database, i.e. the train subset was  
 26 utilized for the training of both the HMM phone models and the fusion models, while the segmentation  
 27 accuracy was measured on the test subset. The SA sentences, which are common for all speakers, were  
 28 excluded from the evaluation. This resulted to eight sentences per speaker, i.e. 3696 and 1344  
 29 sentences in the train and test subsets, respectively. We utilized the well established for American-  
 30 English set of 48 phones, proposed by (Lee and Hon, 1989). Successive occurrences of the same phone  
 31 were merged to one single occurrence as in (Brugnara et al., 1993; Pellom and Hansen, 1998).

32 The phonetic clustering defined in the TIMIT documentation was used: affricates (AFF), fricatives  
 33 (FRI), nasals (NAS), semivowels and glides (GLI), stops (STO), vowels (VOW) and silence (SIL).

34 In the present work the segmentation accuracy was measured in terms of the percentage of  
 35 predicted boundaries within a tolerance of  $t$  milliseconds from the manually annotated boundary labels,  
 36 which is the most commonly used figure of merit. Furthermore, we also present the performances in  
 37 terms of mean absolute errors (MAEs) and root mean squared errors (RMSEs).  
 38

## 39 **4. Experimental Results**

40  
41 We firstly investigated the performance of the BSEs described in Section 3, on the phonetic  
 42 segmentation task. The predictions of these engines per phonetic transition type are further utilized to  
 43 perform the regression fusion scheme shown in Figure 2 for several regression algorithms.  
 44

### 45 **4.1 Results for the Baseline Segmentation Engines**

46  
47 Specifically, first of all, we computed the segmentation accuracy for each BSE separately. The  
 48 performance results, i.e. the amount of correctly detected phonetic boundaries in percentages, for  
 49 different number of HMM states,  $s$ , and Gaussian mixtures,  $m$ , for CI and CD phone models are shown  
 50 in Tables 1 and 2, respectively. In the tables, the setup of each BSE is denoted in brackets as  $[m-s$ -  
 51 CI/CD]. The best performance for each tolerance interval is tabulated in bold. The last two columns in  
 52 Tables 1 and 2 show the performance of each BSE in terms of MAE and RMSE, respectively.  
 53

54  
55 *Table 1*

56  
57 *Table 2*

58  
59

1 As can be seen in Tables 1 and 2, the best performance for all examined tolerances was achieved  
 2 by the HFCC-E speech parameters. In detail, in the [1-4-CI] setup the HFCC-E showed the best  
 3 performance for the tolerances 10 and 30 milliseconds. In contrast to the most widely used MFCC  
 4 features, where the best performance on TIMIT for the tolerance area of 15-25 milliseconds is achieved  
 5 for the setup [1-4-CI], the HFCC-E features demonstrated the best performance for the setup [2-3-CI].  
 6 The differentiation in the segmentation ability between the speech features is owed to the dissimilar  
 7 implementation of the filter-banks among the different speech parameterization methods. For instance,  
 8 while the MFCC filter-bank is based on the Mel-scale, the HFCC-E filter-bank is derived from the  
 9 equivalent rectangular bandwidth (ERB) introduced by (Moore and Glasberg, 1983). Furthermore, in  
 10 the HFCC-E filter-bank the filter bandwidth is decoupled from the filter spacing, which results to a  
 11 smaller overlap among the filters with low centre frequencies and a bigger overlap among the filters  
 12 with high centre frequency, when compared to the filter-bank of the MFCC.

13 As presented in the tables, in most of the cases the CI models outperformed CD models. This is in  
 14 agreement with (Toledano et al., 2003), where it was shown that CI phone models present, in average,  
 15 higher segmentation scores than the CD ones, since the latter tend to lose the alignment with the  
 16 boundaries during training.

17 The experimental results presented in Tables 1 and 2 show that the modelling of the HMM states  
 18 with more than two Gaussian components generally reduces the phonetic segmentation accuracy of the  
 19 BSEs. This is due to the inherent variance of the spectrum in the vicinity of a phonetic transition, which  
 20 could make a simpler model more adequate (Toledano et al., 2003). The superiority of HMMs  
 21 modelled with fewer Gaussians is more intense for small tolerances, while for intermediate and large  
 22 tolerances this tendency is weakened or even inverted, as reported in (Toledano et al., 2003) for  
 23 tolerance equal to 50 milliseconds. Another explanation could be the amount of data in the training  
 24 subset of TIMIT, which might not be sufficient to successfully train with many mixtures the HMM  
 25 states of the phones with few occurrences in the database.

26 The experimental results point out that the best segmentation performance was achieved for the  
 27 HFCC-E BSE, for all the examined tolerances and parameter setups, followed by the PLP and MFCC  
 28 segmentation engines. The advantageous performance of the HFCC-E speech parameters is due to the  
 29 better frequency resolution of their filter-bank at low frequencies. This is in accordance with recent  
 30 insights, which suggest that the human auditory system is capable of a better frequency resolution at  
 31 low frequencies, in comparison to the one incorporated in the Mel-scale, and that resolution continues  
 32 to improve with the decrease of the frequency (Moore, 2003). Indeed, the Mel-scale had been  
 33 approximated with uniform frequency resolution at low frequencies, since at the time it was proposed  
 34 there were only few measurements about the frequency resolution of the human auditory system at low  
 35 frequencies, i.e. [0-500] Hz. Despite the fact that the increasing frequency resolution at low frequencies  
 36 is accounted in some MFCC implementations (Young et al., 2006) and in the implementation of the  
 37 PLP cepstral coefficients, the frequency resolution computed by the ERB is finer and as shown in  
 38 (Moore 2003) is a closer match to the one of the human auditory system.

39 As Tables 1 and 2 show, the best performing BSEs in terms of MAE and RMSE are the HFCC-E  
 40 [1-4-CI] and HFCC-E [6-3-CI] respectively. While the MAE and RMSE statistics generally vary in  
 41 unison, here the presence of outliers in the error distribution generates large values of RMSEs for some  
 42 of the BSEs. The segmentation accuracy shown in Tables 1 and 2 indicates only the averaged  
 43 performance across all the phonetic boundary types in the test subset of TIMIT. A further analysis  
 44 showed that neither the HFCC-E based speech segmentation engine nor the [2-3-CI] setup are the best  
 45 for *every* phonetic class transition type, but only in average among all phone boundary types. Table 3  
 46 shows the best BSE for each boundary type for the most commonly used tolerance of 20 milliseconds.  
 47  
 48

49 **Table 3**

50  
 51  
 52 As can be seen in Table 3, despite the overall performance results shown above, there are phonetic  
 53 boundary types, where other parameterization techniques and setups with higher number of mixtures  
 54 per HMM state and/or context dependent models present superior accuracy. This is due to the fact that  
 55 close to the area of a phone boundary, class specific characteristics such as continuant/non-continuant,  
 56 periodic/non-periodic, short/long duration (Deller et al., 1993) are transitioned from one target articulation  
 57 area to another. Thus, different speech parameterization techniques and BSE setups, with different  
 58 time-frequency resolution, offer different ability to capture the position of specific boundary types,  
 59 even when the same segmentation method is considered (here HMM-based).

1 The evaluation of the BSEs on TIMIT database indicated that the best performing speech features  
 2 are the HFCC-E, which significantly outperformed the widely-used MFCC both in terms of  
 3 segmentation accuracy and in terms of mean absolute error. The superiority of HFCC-E was observed  
 4 across all examined error tolerances. However, since none of the speech features offers advantage for  
 5 all boundary types, a collaborative scheme that exploits the complementary information provided by  
 6 the segmentation engines, employing dissimilar speech features, would contribute to a further  
 7 improvement of the phonetic segmentation accuracy.

#### 10 4.2 Results for the Fusion Schemes

12 The experimental results shown in Table 3 are a clear indication that in order to achieve optimal  
 13 accuracy on the phonetic segmentation task either boundary-specific speech features and BSE setups or  
 14 appropriate fusion schemes, which learn the proper combination function from a representative training  
 15 dataset, have to be employed.

16 Table 4 shows the results obtained after combining the 112 BSEs shown in Tables 1 and 2, with  
 17 the use of the regression fusion algorithms described in Section 2. These algorithms are the support  
 18 vector regression (SVR), the linear regression with the Akaike information criterion, LR(AIC), the  
 19 three-layer multilayer perceptron (MLP) neural network and the model trees (M5'). In addition, we  
 20 present results for three formerly proposed fusion methods: the per boundary type best-only engine  
 21 (BEST) of (Park and Kim, 2006), the average of all predictions (AVE) presented in (Kominek and  
 22 Black, 2004), and the general fusion technique (GFT) proposed in (Jarifi et al., 2008) for the best  
 23 performing case, i.e. the soft supervision case with weighting functions  $f(x)=x$  and  $f(x)=1/(1-x)$ . For the  
 24 purpose of direct comparison with the evaluated fusion algorithms, the best segmentation accuracy  
 25 among the individual BSEs shown in Tables 1 and 2 for each tolerance, MAE and RMSE are  
 26 duplicated in the last row of the table denoted as "No Fusion". The last two columns present the MAE  
 27 and RMSE values. For the GFT and BEST fusion methods the MAE and RMSE values correspond to  
 28 tolerance 20 milliseconds, as these methods use different fusion function and compute different  
 29 boundary predictions for each tolerance.

30 In order to investigate which fusion techniques offer results that are statistically different, in terms  
 31 of MAE, we performed paired *t-test* between all pairs. The *t-test* has also been utilized for the task of  
 32 phonetic segmentation in (Park and Kim, 2007). In Table 4, the similarly coloured cells correspond to  
 33 statistically equivalent results. Finally, the best segmentation accuracy for each tolerance of interest is  
 34 indicated in bold.

37 **Table 4**

38  
 39  
 40 As showed in Table 4, the SVR followed by the LR(AIC) algorithm notably present better  
 41 segmentation accuracy, when compared to the other fusion methods evaluated here. In particular, for  
 42 the tolerance of 15-20 milliseconds, which is considered an acceptable limit for producing good quality  
 43 synthetic speech (Matousek et al., 2003; Wang et al., 2004), the SVR method improved the overall  
 44 segmentation accuracy by approximately 9% in terms of absolute performance. For small tolerances,  
 45 the SVR fusion method offers results which improve the overall segmentation accuracy by more than  
 46 15%, when compared to the best performing BSE, i.e. HFCC-E with setup [1-4-CI]. For large  
 47 tolerances, i.e. about  $\pm 30$  milliseconds, the SVR and LR(AIC) methods improved the absolute  
 48 segmentation accuracy by approximately 5%.

49 The M5' model trees and the MLP NN fusion improved the overall segmentation accuracy for all  
 50 tolerances of interest, with the MLP NN presenting high RMSE, i.e. many large errors, comparing to  
 51 SVR, LR(AIC) and M5' algorithms. On the contrary, the best-only selection, BEST, the averaging of  
 52 the predictions, AVE, and the general fusion technique, GFT, did not improve the segmentation  
 53 accuracy over the one of the best-performing BSEs.

54 All fusion methods were better or similar to the best performing HFCC-E segmentation engine for  
 55 tolerances larger than 20 milliseconds. In this area big misalignments have been obliterated, which is in  
 56 agreement with (Kominek and Black, 2004).

57 Although in earlier studies (Jarifi et al., 2008; Park and Kim, 2006) the GFT and BEST linear  
 58 fusion methods were found to improve the segmentation accuracy on the single-speaker speech  
 59 segmentation task, the experimental results obtained on the TIMIT database demonstrated that in the  
 60 case of multiple speakers these methods do not offer improvement over the accuracy of the best-

1 performing BSE. This is mainly owed to the mismatch between the train and test subsets of TIMIT  
2 (there is no speaker overlap between the train and test subsets), and the variations of the spectral  
3 characteristics of phones among the 630 speakers. These variations are both in the central areas of the  
4 phones and in the transitions between the phones. This mismatch between train and test data results to  
5 different performance of each BSE on the train and test subsets, and thus, the use of the BSEs'  
6 segmentation accuracy on the training data as the criterion for the computation of the fusion parameters  
7  $p(b)$  is not a successful strategy. Moreover, the use of hard decisions, as in the BEST fusion method,  
8 eliminates the predictions of the BSEs with worse segmentation accuracy, which however still include  
9 complementary information that can be exploited for improving the segmentation accuracy.

10 As a result, when phonetic segmentation has to be performed on speech recordings that include  
11 different genders, dialects, multiple speakers, etc, such as in TIMIT database, the computation of the  
12 fusion parameters  $p(b)$  is more efficient, when performed directly from the predictions on training  
13 instances, rather than from the accuracy of each BSE on that training subset. Furthermore, the  
14 experimental results on the TIMIT data indicated that the SVR and LR(AIC) fusion methods offer a  
15 significant advantage over the linear fusion methods used so far, as well as over some non-linear  
16 regression algorithms, and significantly improve the overall phonetic segmentation accuracy. This  
17 improvement derives from the ability of the regression algorithms to capture biases between the real  
18 and the predicted from the BSEs boundary positions, to learn systematic errors of each BSE in specific  
19 phonetic transition types and finally, to better model systematic misalignments in boundary position  
20 predictions between different BSEs.

## 21 22 **5. Conclusion**

23  
24 In this article we proposed the use of a fusion scheme, based on regression analysis, for the task of  
25 phonetic segmentation of speech waveforms. This scheme utilizes numerous independent HMM-based  
26 segmentation engines, with different speech parameterizations, different number of HMM states,  
27 different number of Gaussian mixtures per state, and context dependent and independent models, to  
28 produce multiple predictions of boundary positions. These predictions were utilized as input to the  
29 proposed fusion scheme.

30 Various regression algorithms were evaluated with respect to their capability to provide precise  
31 estimations of the phonetic transition positions. The experimental results demonstrated significant  
32 improvement in the absolute segmentation accuracy for the support vector regression method, when  
33 compared to the best performing baseline segmentation engine. Specifically, in all the evaluated  
34 tolerances the segmentation accuracy was significantly improved, while in the most widely used  
35 tolerance of 20 milliseconds the performance was improved by approximately 9% in terms of absolute  
36 segmentation accuracy. In addition, the mean absolute error was decreased by approximately 33%  
37 while the root mean squared error was reduced by 27%. The linear regression method was found out to  
38 perform slightly worse than the support vector regression method, but also improved the overall  
39 performance by approximately 8%. The experimental results showed that, in the multiple speaker case,  
40 the direct use of the boundary prediction instances resulting from individual segmentation engines on a  
41 training dataset is better than using the accuracies of the segmentation engines on the training dataset  
42 for adjusting the parameters of the fusion scheme.

43 Finally, the support vector regression fusion approach proved to combine segmentation predictions  
44 more successfully, i.e. to provide more precise phonemic boundary position predictions, when  
45 compared to various linear methods reported so far.

## 46 47 **6. Acknowledgement**

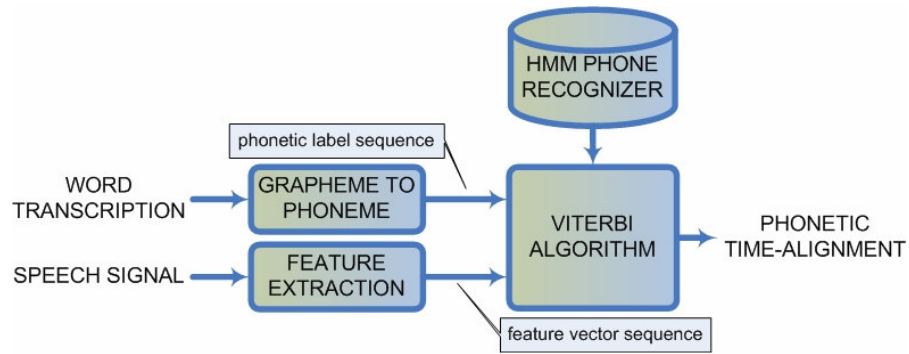
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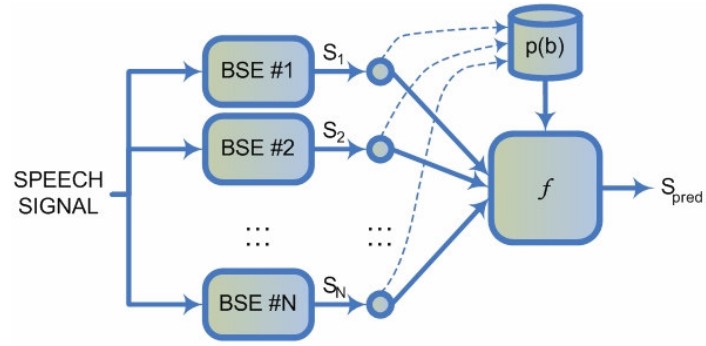


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**Figure 1.** Block diagram of the HMM-based phonetic segmentation method.

ACCEPTED MANUSCRIPT





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**Figure 2.** Block diagram of the regression fusion of multiple baseline segmentation engines (BSEs). The dashed arrows indicate the use of the BSE predictions for the computation of the  $p(b)$  parameters in the training phase.

1 **Table 1.** Segmentation accuracy (in percentages) for the evaluated CI baseline segmentation engines  
 2 (BSEs). Mean absolute error (MAE) and root mean squared error (RMSE) are given in milliseconds.  
 3

[m-s-CI/CD]	BSE	$t \leq 5ms$	$t \leq 10ms$	$t \leq 15ms$	$t \leq 20ms$	$t \leq 25ms$	$t \leq 30ms$	MAE(ms)	RMSE(ms)
[1-3-CI]	HFCC-E	<b>29.85</b>	49.14	66.92	78.57	84.70	88.20	17.05	40.77
	LFCC	19.29	38.14	57.31	72.84	81.25	85.40	19.63	41.60
	MFCC	25.03	44.84	62.12	76.29	83.89	87.65	17.55	37.75
	MWP-ACE	18.94	36.31	55.32	70.19	80.92	85.32	19.76	36.89
	PLP	26.79	46.68	63.71	77.29	84.19	87.87	18.21	43.21
	SBC	21.65	40.73	59.99	74.07	83.49	87.38	19.48	51.27
	WPF	17.78	36.40	56.89	72.30	83.39	87.46	20.15	44.51
[1-4-CI]	HFCC-E	28.92	<b>50.21</b>	66.54	78.54	85.02	<b>88.74</b>	<b>14.98</b>	25.67
	LFCC	20.88	40.96	59.86	74.14	82.44	86.43	18.69	39.59
	MFCC	26.35	47.13	64.25	77.54	84.80	88.63	15.50	26.80
	MWP-ACE	22.16	41.26	60.30	73.33	81.94	86.01	18.50	36.88
	PLP	27.61	48.71	65.34	77.99	84.95	88.62	15.30	26.85
	SBC	21.86	42.65	62.91	76.16	84.54	88.19	16.33	26.15
	WPF	18.15	37.47	58.38	73.42	83.34	87.42	17.77	30.94
[2-3-CI]	HFCC-E	28.40	49.63	<b>68.38</b>	<b>79.41</b>	<b>85.22</b>	88.50	15.03	25.21
	LFCC	21.78	41.70	60.35	73.25	81.90	85.97	19.28	29.23
	MFCC	22.82	42.90	61.20	74.51	83.59	87.41	16.59	25.87
	MWP-ACE	21.58	40.54	59.36	72.87	82.97	86.97	19.86	33.56
	PLP	24.71	45.38	64.14	76.91	84.57	88.02	16.02	27.00
	SBC	20.53	40.12	60.42	74.27	83.31	87.19	18.92	32.23
	WPF	20.80	41.11	62.20	75.71	84.38	88.09	19.10	34.94
[2-4-CI]	HFCC-E	21.63	42.51	62.15	75.79	83.60	87.39	16.47	25.16
	LFCC	18.68	37.01	56.59	71.60	81.20	85.56	18.27	27.98
	MFCC	20.75	40.79	60.29	74.61	82.82	86.90	17.00	27.03
	MWP-ACE	21.26	40.63	59.75	73.67	82.82	86.89	17.35	27.88
	PLP	22.21	42.80	62.32	75.81	83.48	87.26	16.44	26.40
	SBC	19.99	39.10	59.92	74.55	83.48	87.54	16.84	24.74
	WPF	17.38	34.74	55.30	71.20	82.30	86.86	18.29	30.01
[4-3-CI]	HFCC-E	25.84	47.27	66.27	77.93	84.19	87.66	15.22	25.08
	LFCC	22.20	42.40	60.79	73.99	82.43	86.25	19.11	39.96
	MFCC	23.07	43.41	61.80	74.90	83.13	86.89	16.11	24.63
	MWP-ACE	21.50	40.26	58.84	72.53	82.61	86.48	17.52	31.63
	PLP	24.44	45.32	63.71	76.56	83.69	87.14	15.64	24.13
	SBC	19.81	38.96	58.84	72.83	82.41	86.40	16.97	25.83
	WPF	20.80	40.47	61.14	74.92	83.86	87.56	16.21	24.22
[4-4-CI]	HFCC-E	19.85	40.03	59.70	73.08	80.27	84.33	17.41	25.83
	LFCC	18.91	37.79	57.37	71.95	80.04	84.21	17.98	26.81
	MFCC	19.83	39.82	59.11	72.96	80.33	84.56	17.40	25.88
	MWP-ACE	20.61	39.73	59.30	73.25	82.27	86.12	17.18	26.38
	PLP	20.71	41.15	60.50	73.86	80.83	84.92	17.02	25.37
	SBC	18.70	37.64	58.55	72.96	81.96	85.99	17.59	30.86
	WPF	16.29	33.75	54.40	70.14	81.48	85.88	17.89	25.57
[6-3-CI]	HFCC-E	24.53	46.25	65.68	77.60	84.34	87.76	15.18	<b>23.48</b>
	LFCC	21.59	41.14	59.81	73.03	82.02	86.06	18.16	38.37
	MFCC	22.52	42.45	60.96	74.12	82.74	86.64	16.32	24.69
	MWP-ACE	22.20	40.57	58.77	72.57	82.69	86.79	16.88	26.01
	PLP	23.49	43.88	62.55	75.72	83.55	87.27	15.78	24.07
	SBC	20.32	39.07	58.56	72.58	82.23	86.39	16.87	24.92
	WPF	21.20	40.39	60.27	74.19	83.45	87.26	16.32	24.32
[6-4-CI]	HFCC-E	19.05	38.50	58.84	72.67	79.99	84.02	17.72	26.49
	LFCC	19.17	38.51	58.09	72.30	79.44	83.62	18.20	29.03
	MFCC	19.09	38.75	58.41	72.58	80.22	84.44	17.60	26.01
	MWP-ACE	20.36	39.19	58.83	73.11	82.26	86.23	17.66	37.00
	PLP	20.24	40.85	60.54	74.08	81.10	85.17	16.95	25.27
	SBC	17.92	36.29	57.27	72.26	81.45	85.68	17.45	25.29
	WPF	16.06	33.54	54.30	70.10	81.01	85.52	18.03	25.75

1 **Table 2.** Segmentation accuracy (in percentages) for the evaluated CD baseline segmentation engines  
 2 (BSEs). Mean absolute error (MAE) and root mean squared error (RMSE) are given in milliseconds.  
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[m-s-Cl/CD]	BSE	$t \leq 5ms$	$t \leq 10ms$	$t \leq 15ms$	$t \leq 20ms$	$t \leq 25ms$	$t \leq 30ms$	MAE(ms)	RMSE(ms)
[1-3-CD]	HFCC-E	25.29	45.04	63.33	75.97	83.27	87.41	16.81	33.13
	LFCC	18.99	36.44	54.46	69.57	79.49	84.52	18.97	29.56
	MFCC	21.68	40.09	57.99	72.41	81.42	86.22	17.47	27.45
	MWP-ACE	17.78	33.95	53.18	68.67	80.25	85.20	19.60	32.55
	PLP	23.07	42.35	60.46	73.94	81.70	86.16	17.59	32.80
	SBC	19.77	37.34	56.98	71.78	82.72	87.35	17.66	27.65
	WPF	18.08	35.04	55.10	70.29	81.90	86.88	18.34	29.20
[1-4-CD]	HFCC-E	<b>27.09</b>	<b>46.98</b>	<b>64.48</b>	<b>76.09</b>	<b>83.77</b>	<b>87.87</b>	<b>15.64</b>	<b>25.28</b>
	LFCC	19.40	38.08	56.11	70.41	80.57	85.56	19.46	39.41
	MFCC	23.16	42.75	60.33	74.16	82.72	87.26	16.59	25.97
	MWP-ACE	21.58	40.37	58.93	72.19	81.90	86.21	18.33	35.21
	PLP	25.77	45.21	61.59	74.71	82.83	87.20	16.28	25.91
	SBC	21.43	41.16	60.57	74.36	83.75	88.02	16.70	26.05
	WPF	17.56	35.03	54.77	70.16	81.51	86.63	18.34	29.00
[2-3-CD]	HFCC-E	25.25	44.43	62.49	74.30	82.51	86.89	16.51	26.69
	LFCC	19.87	37.44	54.89	68.93	79.09	84.18	19.42	35.66
	MFCC	21.63	39.28	56.36	70.07	79.74	85.00	17.88	27.12
	MWP-ACE	18.63	34.73	53.23	68.32	80.32	85.55	19.18	31.48
	PLP	23.39	42.13	59.56	72.11	80.50	85.36	17.47	27.98
	SBC	19.80	36.93	55.70	70.37	81.75	86.69	17.87	27.06
	WPF	18.14	35.01	54.05	69.11	81.42	86.37	18.56	29.65
[2-4-CD]	HFCC-E	25.32	45.04	62.57	74.59	82.55	86.88	16.39	26.97
	LFCC	18.31	35.95	54.15	68.62	79.06	84.27	18.99	30.96
	MFCC	21.74	40.67	58.25	71.60	80.99	85.88	17.37	26.51
	MWP-ACE	20.77	39.19	57.98	71.57	81.53	86.06	17.88	28.88
	PLP	24.26	43.29	59.81	72.32	81.39	86.00	16.93	26.21
	SBC	20.34	39.05	58.68	72.59	82.41	87.06	17.28	26.56
	WPF	15.78	32.10	51.68	67.58	79.38	84.77	19.32	29.47
[4-3-CD]	HFCC-E	24.52	42.80	59.75	71.76	80.33	85.02	17.21	27.89
	LFCC	19.77	36.97	53.45	67.03	77.40	82.69	19.12	29.32
	MFCC	21.24	38.37	54.82	68.20	77.85	83.25	18.34	27.61
	MWP-ACE	19.00	35.13	53.17	67.84	79.63	84.67	18.89	30.81
	PLP	22.74	40.70	57.63	70.20	78.90	83.80	17.86	27.78
	SBC	19.56	36.38	54.53	68.54	79.86	84.97	18.17	27.35
	WPF	18.34	35.04	53.37	67.84	79.69	84.86	19.03	34.14
[4-4-CD]	HFCC-E	23.89	43.06	60.67	72.74	80.82	85.31	16.83	26.88
	LFCC	17.75	34.66	52.60	66.87	77.08	82.53	19.16	28.13
	MFCC	20.66	38.60	55.84	69.03	78.10	83.27	18.21	27.80
	MWP-ACE	19.98	37.91	56.37	70.02	79.57	84.44	18.20	29.13
	PLP	22.62	41.44	58.04	70.16	78.75	83.78	17.66	27.27
	SBC	19.20	37.33	56.45	70.22	80.12	84.87	18.00	27.67
	WPF	15.62	31.56	50.55	66.17	77.94	83.42	19.44	29.11
[6-3-CD]	HFCC-E	24.03	41.87	58.77	70.98	79.73	84.54	17.47	27.88
	LFCC	19.56	36.55	52.65	66.03	76.45	81.85	20.04	39.55
	MFCC	20.97	37.60	54.14	67.52	77.25	82.74	18.68	28.37
	MWP-ACE	18.99	35.16	53.09	67.91	79.57	84.87	18.62	28.70
	PLP	22.11	40.06	56.85	69.10	78.00	83.17	18.23	28.30
	SBC	19.50	36.45	54.23	68.26	79.56	84.73	18.22	27.22
	WPF	18.12	34.71	52.80	67.51	79.41	84.78	18.96	32.63
[6-4-CD]	HFCC-E	23.40	42.60	60.45	73.05	80.52	84.97	17.10	28.70
	LFCC	17.60	34.50	52.17	66.58	76.25	81.86	19.39	28.30
	MFCC	19.84	37.77	55.12	68.27	77.44	82.76	18.59	29.00
	MWP-ACE	19.72	37.54	56.04	69.69	79.11	84.15	18.32	29.26
	PLP	22.02	40.74	57.13	69.54	78.03	83.07	17.98	27.58
	SBC	18.97	36.54	55.64	69.88	79.68	84.55	18.13	27.29
	WPF	15.65	31.70	50.51	66.22	77.72	83.21	19.46	28.95

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1 **Table 3.** Best BSE per phonetic transition type for 20 milliseconds tolerance. Rows and columns  
 2 indicate the left (L) and right (R) context of the phonetic boundary, respectively.  
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L\R	AFF	FRI	NAS	GLI	SIL	STO	VOW
AFF	MFCC[1-3-Cl]	PLP[6-3-CD]	MFCC[1-3-CD]	MWP-ACE[4-4-CD]	MWP-ACE[4-4-Cl]	HFCC-E[1-3-CD]	PLP[6-4-CD]
FRI	HFCC-E[1-3-CD]	HFCC-E[4-4-Cl]	HFCC-E[1-4-CD]	HFCC-E[1-4-Cl]	MFCC[2-3-Cl]	SBC[1-3-CD]	HFCC-E[2-4-CD]
NAS	HFCC-E[1-4-Cl]	HFCC-E[2-3-CD]	HFCC-E[1-4-CD]	HFCC-E[2-4-CD]	HFCC-E[4-4-Cl]	PLP[4-3-Cl]	PLP[2-4-CD]
GLI	WPF[1-3-CD]	WPF[2-4-CD]	MFCC[2-4-CD]	PLP[2-4-CD]	HFCC-E[4-4-Cl]	WPF[2-4-CD]	PLP[6-4-CD]
SIL	HFCC-E[1-3-Cl]	HFCC-E[1-3-Cl]	MWP-ACE[1-4-Cl]	HFCC-E[1-3-Cl]	-	HFCC-E[1-3-Cl]	HFCC-E[1-3-Cl]
STO	MWP-ACE[1-3-Cl]	HFCC-E[4-4-CD]	HFCC-E[1-4-Cl]	HFCC-E[1-4-Cl]	LFCC[4-3-Cl]	WPF[1-4-Cl]	HFCC-E[2-4-CD]
VOW	HFCC-E[1-3-Cl]	MWP-ACE[1-4-CD]	PLP[1-4-CD]	PLP[1-4-CD]	SBC[6-4-Cl]	HFCC-E[2-4-Cl]	PLP[1-4-Cl]

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1 **Table 4.** Phone segmentation using regression fusion algorithms for 112 BSEs.

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Fusion Method	$t \leq 5\text{ms}$	$t \leq 10\text{ms}$	$t \leq 15\text{ms}$	$t \leq 20\text{ms}$	$t \leq 25\text{ms}$	$t \leq 30\text{ms}$	MAE(ms)	RMSE(ms)
SVR	<b>45.30</b>	<b>71.43</b>	<b>82.28</b>	<b>88.18</b>	<b>91.68</b>	<b>94.01</b>	<b>10.01</b>	<b>17.15</b>
LR(AIC)	43.01	68.74	80.52	87.12	91.03	93.54	10.44	17.47
MS'	39.85	63.05	78.07	84.31	88.37	91.28	11.95	19.82
MLP	34.27	57.92	72.23	80.40	86.64	89.85	13.91	27.56
GFT [ $f(x)=1/(1-x)$ ]	20.76	41.98	62.26	76.83	85.40	89.48	15.49	23.24
GFT [ $f(x)=x$ ]	21.48	41.89	61.79	75.86	84.47	88.81	15.90	24.16
BEST	24.69	46.27	65.26	76.41	86.05	90.23	15.84	33.78
AVE	20.21	40.50	60.75	75.22	84.25	88.80	15.96	23.59
No Fusion	29.85	50.21	68.38	79.41	85.22	88.74	14.98	23.48

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