Acoustic Landmarks Contain More Information About the Phone String than Other Frames

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Abstract

Most mainstream Automatic Speech Recognition (ASR) systems consider all feature frames equally important. However, acoustic landmark theory is based on a contradictory idea, that some frames are more important than others. Acoustic landmark theory exploits the quantal non-linear articulatory-acoustic relationships from human speech perception experiments, and provides theoretical support for extracting acoustic features in the vicinity of landmark regions where an abrupt change occurs in the spectrum of speech signals. In this work, we conduct experiments on the TIMIT corpus, with both GMM and DNN based ASR systems and found that frames containing landmarks are more informative than others. We found that altering the level of emphasis on landmarks through accordingly re-weighting acoustic likelihood in frames, tends to reduce the phone error rate (PER). Furthermore, by leveraging the landmark as a heuristic, one of our hybrid DNN frame dropping strategies maintained a PER within 0.44\% of optimal when scoring less than half (41.2\% to be precise) of the frames. This hybrid strategy out-performs other non-heuristic-based methods and demonstrates the potential of landmarks for reducing computation.

Keywords: Automatic Speech Recognition; Acoustic Landmarks; Distinctive Features

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I. INTRODUCTION

Acoustic Landmark theory (Stevens, 1985, 2000) exploits the quantal non-linear articulatory-acoustic relationships garnered from human speech perception experiments to define instances in time (landmarks) at which abrupt change or local extrema occur in both speech articulation and the speech spectrum. Landmark theory proposes that humans perceive phonemes in response to acoustic cues, and that such cues are anchored temporally at landmarks, i.e., that a spectrotemporal pattern is perceived as the cue for a distinctive feature only if it occurs with a particular timing relative to a particular type of landmark. Altering distinctive features alters the phone string, distinctive features in turn get signaled by different sets of cues anchored at landmarks.

Recent advances with neural networks have resulted in significant performance gains for modern ASR systems (Xiong et al., 2016), but in fact they may not actually make much use of ideas from speech science. This could be unfortunate as findings from speech science could potentially improve the performance of these systems. Such systems extract feature vectors at regular time intervals, usually with a multi-dimensional log-filterbank spaced evenly along the Mel-frequency domain. Vectors from adjacent frames may be concatenated to provide more temporal context. These systems assume that every frame is equally important, and rely on a backend decoder to integrate information from frame to frame. Mel-frequency mapping is an approximate implementation of critical band theory (Fletcher and Munson, 1933), but otherwise, the acoustic models (AM) of these systems are implemented with simple machine learning algorithms, with little or no reference to current models of human speech perception. Recently, end-to-end systems based on connectionist temporal classification (CTC) for long-short term memory (LSTM) AMs (Sak et al., 2015) have demonstrated advantages over traditional models such as Gaussian Mixture Models (GMM) and Deep Neural Networks (DNN), moving away from the frame-synchronous approaches which place equal emphasis on each frame. When properly trained with sufficient data, a CTC-LSTM gains the ability to recognize speech, but very little qualitative knowledge can be extracted from the resulting model.

The theory of acoustic-landmark based speech perception has inspired a large number of ASR systems (Hasegawa-Johnson et al., 2005, Jansen and Niyogi, 2008, Juneja, 2004), many with accuracy comparable to other contemporaneous ASR systems. All landmark inspired
ASR systems operate on a set of acoustic landmark classifiers that label distinctive features by detecting their correlated acoustic cues. Since acoustic correlates vary dramatically from one distinctive feature to another, there usually does not exist a “one-for-all” detector or classifier \cite{Jansen and Niyogi, 2008}. That said, MFCC has demonstrated its effective as a good candidate feature in some applications. Qian, Zhang, and Hasegawa-Johnson \cite{2016}, for example, leveraged spliced MFCC features to detect stop consonant landmarks with an error rate lower than 5%. Results of this sort inspire an attempt to measure the information content of landmarks using an MFCC-based ASR.

We assume that a well trained statistical AM that has learned the association between MFCC features and triphones, has also included sufficient cues and necessary contexts to associate MFCCs and distinctive features. What then prevents these cues and contexts from giving us better ASR accuracy, is the limitation of our frame-synchronous model – that in fact if we treat some frames as more important than others we can get better accuracy, In other words, our experiments described in this paper try to answer this question: are frames containing acoustic landmarks more important than other frames for modern ASR?

We present two methods to quantify the information content of phonetic landmarks. The first is to over-weight the AM likelihood scores of frames containing phonetic landmarks. By over-weight, we mean multiplying log-likelihoods with a value larger than 1, more details presented in Section III A. The second method is to “remove” frames from the ASR input. Furthermore, we take the approach of reducing computation as much as possible with minimal accuracy loss - that is we examine the increase in PER as we remove different types of frames from our decoding. We searched for a strategy to remove as many frames as possible while attempting to keep the PER low. We show that if we know the locations of acoustic landmarks, and if we retain these frames while dropping others, it is possible to reduce computation for ASR systems with small error increment penalty. This method for testing the information content of acoustic landmarks is based on past works \cite{Iso-Sipilä, 2000, McGraw et al., 2016, Vanhoucke et al., 2013} that demonstrated significantly reduced computation by dropping acoustic frames, with small increases in PER depending on the strategy used to drop frames; in this paper we adopt the PER increment as an indirect measure of the phonetic information content of the dropped frames.

In addition to answering the question proposed above, this work also seeks to find a practical application for landmark in ASR. That is to find out, assuming landmark proved
to be informative to ASR, if the former can reduce computational load, at very low accuracy cost, by informing the more useful frames to the latter. It is worth emphasizing that this work only intends to explore this potential application, assuming landmarks can be accurately detected. Our actual landmark detection accuracy, despite increasing over time, has not reach a practical level yet.

In this paper, Section II briefly reviews the acoustic landmark theory and relevant works which apply it to ASR systems. Section III presents the theoretical basis for our experiments. Section IV proposes the hypothesis. Experimental setup is explained in Section V and results are presented in Section VI. Discussion, including a case study of the confusion characteristics is presented in Section VII and our conclusions are drawn in Section VIII.

II. BACKGROUND AND LITERATURE REVIEW

Speech processing systems based on acoustic landmark theory differ from other ASR systems on one major point. The minimal speech entity that latter systems decode is the triphone (Lee, 1988), while a landmark-based system operates on distinctive features. Distinctive features are an approximately binary encoding of perceptual (Jakobson et al., 1951), phonological (Chomsky and Halle, 1968), and articulatory (Stevens, 1985) speech sound categories. Each phone or phoneme is described using a vector of binary distinctive feature. Though phonemes are language-dependent, distinctive features can be designed to be universal (Stevens, 2002, Stevens et al., 1986), and a phoneme can be defined to be a set of phones used indistinguishably by the speakers of a language (Stevens et al., 1986).

The ASR community has explored a number of encodings similar to distinctive features, but with less precise phonological definitions, e.g., articulatory features (Kirchhoff, 1998, 1999, Kirchhoff et al., 2002, Livescu et al., 2007, Metze, 2005, Naess et al., 2011) and speech attributes (Lee et al., 2007). These concepts have different foci, but they also share considerable similarity. Loosely speaking, articulatory features are a subset of distinctive features. While distinctive features are defined to be speech sound categories with language-independent articulatory and/or acoustic correlates and language-dependent phonological correlates, articulatory features only focus on the subset of this list that can be unambiguously defined by their articulatory correlates. Many papers (Kirchhoff, 1998, Kirchhoff et al., 2002, Livescu et al., 2007, Metze, 2005, Naess et al., 2011) have focused on articu-
atory features in order to anchor sound categories in a language-independent phenomenon (articulation), thus making it easier to adapt to different human speaking styles. Speech attributes, on the other hand, are a super-set of distinctive features. The former are deliberately defined to incorporate other purposes into speech recognition. In Lee’s framework (Lee et al., 2007), speech attributes are quite broadly defined to be perceptible speech categories, of which phonological categories are only a subset. Under this definition, speech attributes include not only distinctive feature but also a wide variety of acoustic cues signaling gender, accent, emotional state and other prosodic, meta-linguistic, and para-linguistic messages.

As opposed to modern statistical ASR where each frame is treated with equal importance, landmark theory proposes that there exist information rich regions in the speech utterance, and that we should focus on these regions more carefully. These regions of interest are called acoustic landmarks. Landmarks are regions within the utterance where distinctive features are most clearly signaled. These key points mark human perceptual foci and key articulatory events (Liu, 1996). Stevens (1985) first introduced these sub-segments of the speech utterance, where for some phonetic contrasts, humans would focus in order to extract acoustic cues necessary for identifying the underlying distinctive features. Initially Stevens named these key points “acoustic boundaries”; the name “acoustic landmarks” was introduced in 1992 (Stevens et al.), and has been used consistently since. Roughly at the same time Furui (1986) and Ohde (1994) made similar observations when studying children’s speech perception in Japanese.

The location of acoustic landmarks in speech utterances was studied from an information theory perspective in a paper by Hasegawa-Johnson (2000). Early work (Liu, 1996) considered landmark location for the purpose of data labeling, but Hasegawa-Johnson (2000) later backed these findings up experimentally. In his work, Hasegawa-Johnson (2000) defined a set of landmarks including consonant releases and closures, at boundaries of the corresponding phones, and vowel/glide pivot landmarks, near the center of the corresponding phones. In contrast, Lulich (2010) argued that center of vowels and glides are not as informative and should not be considered as landmarks. He defined, instead, formant-subglottal resonance crossing, which is known to sit between boundaries of [-back] and [+back] vowels, to be more informative. In a paper, ? showed that the latter improves performance for automatic speaker normalization application. A small number of pivot and release landmarks were defined at +33% and −20% locations after the beginning or before the end of certain
phones, in order to better approximate the typical timing of the spectrotemporal events defined earlier in Liu’s work [Liu 1996]. Later works [Hasegawa-Johnson et al. 2005 Kong et al. 2016], labeled these landmarks right on the boundary for consistency and returned similar performance. Figure 1 illustrated the landmark labels for the pronunciation of word “Symposium” [1]. The detail of landmark labeling heuristics applied in this example is further described in Table 1.

**FIG. 1:** Acoustic landmark labels for the pronunciation of word “Symposium”. TIMIT alphabetical symbols of phones and IPA symbols are used in this example. The dashed red lines denote the landmark positions. The symbols under the dashed red lines are landmark types, where FC and FR are closure and release for fricatives; SC and SR are closure and release for Stops; NC and NR are closure and release for nasals; V and G are vowel pivot and glide pivot; MC is manner-change landmark.

Many works have focused on accurately detecting acoustic landmarks. The first of these assumed that landmarks correspond to the temporal extrema of energy or energy change in particular frequency bands, e.g., Liu (1996) detected consonantal landmarks in this way, Howitt (2000) detected vowel landmarks, Choi (1999) classified consonant voicing, and Lee and Choi (2008a), Lee et al. (2011, 2012), Lee and Choi (2008b) classified place of articulation. Support Vector Machines (SVMs) were popularized for landmark detection by Niyogi, Burges, and Ramesh (1999), who showed that an SVM trained to observe a very small acoustic feature vector (only four measurements, computed once per millisecond) can

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1 The pronunciation of “Symposium” is selected from audio file: TIMIT/TRAIN/DR1/FSMA0/SX361.WAV
detect stop release landmarks more accurately than a hidden Markov model. Both Borys (2008) and Chitturi and Hasegawa-Johnson (2006) target the detection of all landmarks using one kind of acoustic features. Their results are reasonably accurate, but are still less accurate and more computationally expensive than the best available classifier for each distinctive feature. Xie and Niyogi (2006) expanded the work of Niyogi, Burges, and Ramesh (1999) by demonstrating detection of several different types of landmark using a very small acoustic feature vector. In Qian’s paper (Qian et al., 2016), a small vector of acoustic features was learned, using the technique of local binary patterns, and resulting in accuracy above 95% for stop consonant detection. In a paper from Kong et al. (2016), a Convolutional Neural Network (CNN) trained on MFCC and additional acoustic features achieved around 85% on consonant voicing detection. This system was trained on the English corpus TIMIT (Garofalo et al., 1993), but tested on Spanish and Turkish corpora. Over time, new techniques and more specific features have been developed for landmark detection, and the detection accuracy has been improving steadily. Acoustic landmarks were first introduced as part of an ASR in 1992 (Stevens et al.), and have been used in a variety of ASR architectures. These systems, without considering the mechanism used for landmark detection, can be incorporated into two types. The first type of system, such as that from Jansen and Niyogi (2008), Juneja (2004), Liu (1996) computes a lexical transcription directly from a set of detected distinctive features. Due to the complexity of building a full decoding mechanism on distinctive features, some of these systems only output isolated words. However, other systems (e.g., work from Jansen and Niyogi (2008)) have full HMM back-ends that can output word sequences. The other type of system, such as the one from Hasegawa-Johnson et al. (2005), conducts landmark-based re-scoring on the lattices generated by an MFCC-based hidden Markov model. Acoustic likelihood from the classic ASR systems are adjusted by the output of the distinctive feature classifier. Many landmark based ASRs demonstrated performance slightly (Hasegawa-Johnson et al. 2005) or even significantly (Kirchhoff, 1998) better than baseline ASR systems, especially in noisy conditions.

III. MEASURE OF INCORPORATING PHONETIC INFORMATION

In terms of classifying the distinctive features anchored at acoustic landmarks, a long temporal window is beneficial. By definition, an acoustic landmark is an instantaneous
event that serves as a reference time point for the measurement of spectrotemporal cues widely separated in time and frequency. For example, in the paper that first defined phonetic landmarks, Stevens proposed classifying distinctive features of the landmark based on the onsets and offsets of formants and other spectrotemporal cues up to 50ms before or 150ms after the landmark (Stevens, 1985). The 200ms spectrotemporal dynamic context proposed by Stevens is comparable to the 185ms spectrotemporal dynamic context computed for every frame by the ASR system of Veselý et al. (2013). Most ASR systems decode using frames lasting 25ms, with a 10ms skip, as human speech is quasi-stationary for this short period (Quatieri, 2008). On paper, a duration of 25ms falls short for distinctive feature classification. Because spectral dynamics communicate distinctive features, however, ASR systems since 1981 (Furui) have used dynamic features. Experiments reported in this paper are built on a baseline described by Veselý et al. (2013), in which MFCCs are computed once per 10ms, with 25ms windows. The dark gray rectangles in Fig 2 represent a frame of speech spanning 25 ms, regularly sampled at 10ms intervals. In order to include more temporal context, we stack adjacent frames (with red frame being the center frame), three preceding and three succeeding frames for a total of seven frames (a total temporal span of \((7 - 1) \times 10 + 25 = 85\)ms), together. The seven-frame stack is projected down to 40 dimensions using linear discriminant analysis (LDA). In fact, empirical studies have found frame stacking to return higher accuracy compared to single-frame-features. This trend not only applies to stacking below 100ms. With careful normalization, features like TRAPs (Herman-sky, 2003), with temporal window equal or longer than 500ms, continuous to demonstrate accuracy improvement. For input to the DNN but not the GMM, LDA is followed by speaker adaptation using mean subtraction and feature-space maximum likelihood linear regression, additional context is provided by a second stacking operation afterwards, in which LDA-transformed features, represented by yellow rectangles, are stacked +/-5 frames (for a total temporal span of \((11 - 1) \times 10 + 85 = 185\)ms), as represented by the top path in Fig 2. It is believed that the reason features spanning longer duration benefits ASR system is long lasting features capture coarticulation better. Subconsciously planned coarticulation, as opposed to surface level coarticulation, can affect one or even a couple of syllables in advance. For example, if a syllable-final consonant requires nasalization, lip rounding or /r/ tongue shape, they will almost always start near the beginning of the preceding vowel.

The wide temporal windows used in modern ASR are therefore highly useful to landmark-
based speech recognition, since information from discarded frames is not completely lost, but preserved in the surrounding kept frames (Sak et al. 2015).

A. Frame re-weighting

HMM-based LVCSR searches the space of all possible state sequences for the most likely state sequence given the observations. During the state likelihood estimation, results of all frames are weighted equally. Weighting more informative frames over other could potentially benefit speech recognition. Ignoring the effects of the language model, the log-likelihood of a state sequence $S$ given the observations $O$ is

$$L(S|O) = \sum_{t=1}^{T} w(t) \log(p(o_t|s_t)) + \log(p(s_t, s_{t-1})),$$  \hspace{1cm} (1)

where $s_t$ and $o_t$ are respectively the state and observed feature vector associated with the frame at time $t$. The state $s_t$ at any time should be associated with one of the senones (i.e., monophone or clustered triphone states). Here $p(s_t, s_{t-1})$ is the transition probability between senones, which we will not consider modifying in this study. In GMM systems, beam search parameters constrain the number of active states, thus we only need to evaluate the necessary posteriors. In DNN-based models usually all posteriors are evaluated. In our over-weighting framework, if $o_t$ contains a landmark, the value of $p(o_t|s_t)$ will be increased. To simplify the computation, we operated directly on log-likelihoods. In this case, $\log(p(o_t|s_t))$ is multiplied by factor $w(t)$ which takes the value 1 when frame $t$ contains no landmark and a value greater than 1 otherwise. This is effectively applying a power operation on the
The key in this strategy is that the likelihood of all model states will be re-weighted. If the frame over-weighted is a frame that can differentiate the correct state better, the error rate will drop. In contrast, if the likelihood of a frame is divided evenly across states, or even worse, prefers the incorrect state, then over-weighting this frame will mislead the decoder and increase chances of error. For this reason, over-weighting landmark frames is a good measure to tell how meaningful landmark frames are compared to the rest of the frames. If the landmarks are indeed more significant, we should observe a reduction in the PER for the system over-weighting the landmark.

B. Frame dropping

Our different frame dropping heuristics modify the cost for a state sequence by replacing the posterior probability \( p(o_t|s_t) \) with an approximation function \( f \). In terms of cost or minus log probabilities, Equation (1) becomes

\[
L(S|O) = \sum_{t=1}^{T} \log f(p(o_t|s_t), t) + \log(p(s_t, s_{t-1})),
\]

The class of optimizations considered in this paper involve a set of functions \( f(p(o_t|s_t)) \) parameterized as:

\[
f(p(o_t|s_t)) = \begin{cases} 
R(O,t) & \text{if } g(t) = 1 \\
p(o_t|s_t) & \text{otherwise}
\end{cases}
\]

The method of replacement is characterized by \( R \), and the frame-dropping function by \( g(t) \). This work considers four (multiple methods are consider to verify that finding with respect to landmark is independent of the replacement method) possible settings of the \( R(O,t) \) function, as follows:

\[
R(O,t) \in \begin{cases} 
R_{\text{Copy}}(O,t) = p(o_{t'}|s_{t'}), & t' = \max_{\tau \leq t, g(\tau)=0} \tau \\
R_{\text{Fill},0}(O,t) = 1 \\
R_{\text{Fill},\text{const}}(O,t) = \left( \prod_{t=1}^{T} p(o_t|s_t) \right)^{1/T} \\
R_{\text{Upsample}}(O,t) = \exp \left( \sum_{t':g(t')=0} h(t - t') \log p(o_t|s_t) \right)
\end{cases}
\]
In other words, the **Copy** strategy copies the most recent observed value of \( p(o_t|s_t) \), the **Fill \_0** strategy replaces the log probability by 0, the **Fill \_const** strategy replaces the log probability by its mean value, and the **Upsample** strategy replaces it by an interpolated value computed by interpolating (using interpolation filter \( h(t) \)) the log probabilities that have been selected for retention. The **Upsample** strategy will only be used if the frame-dropping function is periodic, i.e., if frames are downsampled by a uniform downsampling rate.

The *pattern of dropped frames* can be captured by the indicator function \( g \), which is true for frames that we want to drop. Experiments will test two landmark-based patterns: **Landmark-drop** drops all landmark frames \( (g(t) = 1 \text{ if the frame contains a landmark}) \), and **Landmark-keep** keeps all landmark frames \( (g(t) = 1 \text{ only if the frame does not contain a landmark}) \). In the case landmark information is not available, frame-dropping pattern may be **Regular**, in which \( g(t) = \delta( t \mod K ) \) indicating that every \( K \)-th frame is to be dropped, or it may be **Random**, in which case the indicator function is effectively a binary random variable set at a desired frame dropping rate. As we will demonstrate later, to achieve a specific function and dropping ratio, we can sometimes combine output of different \( g \) functions together by taking a logical inclusive OR to their output.

If acoustic landmark frames contain more valuable information than other frames, it can be expected that experiment setups that retain the landmark frames should out-perform other patterns, while those that drop the landmark frames should under-perform, regardless of the *method of replacement* chosen.

**IV. HYPOTHESES**

This paper tests two hypotheses. The first is that a window of speech frames (in this case 9 frames) centered at a phonetic landmark has more information than windows centered elsewhere – this implies that over-weighting the landmark-centered windows can result in a reduction in PER. The second hypothesis states that keeping landmark-centered windows rather then other windows causes little PER increment, and that dropping a landmark-centered window causes greater PER increment as opposed to dropping other frames. In the study we focused on PER as oppose to Word Error Rate (WER) for 2 reasons, first the baseline Kaldi recipe for TIMIT reports PER; second, this study orients acoustic science, focusing on phones allow us to categorize and discuss the experiment and results in better
context.

TABLE I: Landmark types and their positions for acoustic segments. \( Fc \) and \( Fr \) are closure and release for fricatives; \( Sc \) and \( Sr \) are closure and release for Stops; \( Nc \) and \( Nr \) are closure and release for nasals; \( V \) and \( G \) are vowel pivot and glide pivot; ‘start’, ‘middle’, and ‘end’ denote three positions across acoustic segments.

| Manner of Articulation | Landmark Type and Position | Observation in Spectrogram |
|------------------------|---------------------------|-----------------------------|
| Vowel                  | V: middle                 | maximum in low- and mid-frequency amplitude |
|                        | G: middle                 | minimum in low- and mid-frequency amplitude |
| Fricative              | Fc: start, Fr: end        | amplitude discontinuity occurs when consonantal constriction is formed or released |
| Affricate              | Sr,Fc: start, Fr: end     |                             |
| Nasal                  | Nc: start, Nr: end        |                             |
| Stop                   | Sc: start, Sr: end        |                             |

In order to test these hypotheses, a phone boundary list from the TIMIT speech corpus (Garofalo et al. 1993) is obtained, and we label the landmarks based on the phone boundary information. Table I briefly illustrates the types of landmarks and their positions, as defined by the TIMIT phone segments. This marking procedure is shared by Hasegawa-Johnson et al. (2005), Kong et al. (2016), Stevens (2002). It is worth mentioning that this definition disagrees with that from Lulich (2010). Lulich claims that there is no landmark in the center of Vowel and Glide; instead, formant-subglottal resonance crossing, which is known to sit between boundary of [−Vowel] and [+Vowel] contains a landmark. Frames marked as landmark are of interest. To test hypothesis 1, landmark frames are over-weighted. To test hypothesis 2, either non-landmark or landmark frames, are dropped.

V. EXPERIMENTAL METHODS

Our experiments are performed on the TIMIT corpus. Baseline systems use standard examples distributed with the Kaldi open source ASR toolkit\(^2\). Specifically, the GMM-based baseline follows the configurations in the distributed \texttt{tri2} configuration in the Kaldi TIMIT example files\(^3\). The clustered triphone models are trained using maximum likelihood estimation, linear discriminant analysis and maximum likelihood linear transform was applied. For the DNN baseline, speaker adaptation is performed on the features, and nine consecutive frames centered at the current frame are stacked as inputs to the DNN, as specified in

\(^2\) [http://kaldi-asr.org/](http://kaldi-asr.org/)
\(^3\) [https://github.com/kaldi-asr/kaldi/tree/master/egs/timit/s5](https://github.com/kaldi-asr/kaldi/tree/master/egs/timit/s5)
the distributed tri4_nnet example. Respectively, the two systems achieved PER of 23.8% (GMM) and 22.6% (DNN) without any modification.

We performed a 10-fold cross validation (CV) over the full corpus, by first combining the training and test sets, and creating 10 disparate partitions for each test condition. The gender balance was preserved to be identical to the canonical test set for each test subset, while the phonetic balance was approximately the same but not necessarily identical. This is in order to improve the significance of our PER numbers. The TIMIT corpus is fairly small and the phone occurrence of some phones, or even phone categories, in the test set is lower than ideal. Conducting cross validation on the full set allows us partially address this issue.

For the control experiments of our tests, all configurations of feature extraction and decoding process are retained the same as the baseline. In this case, fair comparisons are guaranteed, and we can fully reveal the effects of our methods in the AM scoring process.

VI. EXPERIMENTAL RESULTS

Experimental results examining the two hypotheses proposed above will be presented in this section. We will present the results of over-weighting the landmark frames first. Evaluation of frame dropping will be presented second, and includes several phases. In the first phase, a comparison of different methods of replacement is presented, to provide the reader with more insight into these methods before they are applied to acoustic landmarks. In the second phase, we will then leverage our findings to build a strategy that both drops non-landmark frames, and over-weights landmark frames, using the best available pattern of dropped frames and method of replacement.

A. Hypothesis 1: Over-weighting Landmark Frames

Figure 3 illustrates the PER of the strategy of over-weighting the landmark frames during the decoding procedure, and how it varies with the factor used to weight the AM likelihood of frames centered at a landmark. The PER for GMM-based models drops as the weighting factor increases until the factor is 1.5; increasing the weighting factor above 1.5 causes the PER to increase slightly. When the factor is increased to greater than 2.5, the PER increases
at a higher slope. Similar trends can be found for DNN models, yet in this case the change in PER is non-concave and spans a smaller range. If landmark frames are under-weighted, or over-weighted by a factor of 1.5 or up to 2.0, PER increases. Over-weighting landmark frames by a factor of 3.0 to 4.0 reduces PER. Hypothesis tests (Gillick and Cox 1989) have been conducted and neither of the PER reductions (GMM or DNN) are statistically significant. In this experiment, Wilcoxon tests (Gillick and Cox 1989) have been conducted, through Speech Recognition Scoring Toolkit (SCTK) 2.4.10[^4] and tests concluded the difference to be insignificant.

![Graph of GMM and DNN over-weighting](image)

**FIG. 3:** Over-weighting landmark frames for GMM and DNN.

[^4]: [https://www.nist.gov/itl/iad/mig/tools](https://www.nist.gov/itl/iad/mig/tools)
B. Methods of Replacement for Dropped Frames

Figure 4 compares the performance of three methods of replacement: Copy, Fill_0 and Fill_const when a Regular frame dropping pattern is used. Results show that Fill_0 and Fill_const suffer very similar PER increments as the percentage of frames dropped is increased, while Copy shows a relatively smaller PER increment for drop rates of 40% or 50%. As for the comparison between acoustic models, DNN-based models outperform GMM-based at all drop rates. Notably, the Copy approach synergizes well with DNN models, and is able to maintain low PER increments even up to 90% drop rate; this finding is similar to findings reported in papers from Vanhoucke et al. (2013).

![Comparison of Different Methods of Frame Replacement](image)

**FIG. 4:** Comparison of Different Methods of Frame Replacement (Copy, Fill_0 and Fill_const) assuming a Regular pattern of frame replacement.

Figure 5 compares the performance between two patterns of dropping frames – Regular, Random. In both of these the Copy method for replacement was used. We also provide for comparison, the Regular pattern, but using an Upsample replacement method. This scheme
uses a 17-tap anti-aliasing FIR filter. The method that offered the lowest phone error rate increment is obtained using a Regular pattern with a Copy replacement scheme. Results show that Regular-Copy outperforms other methods by a large margin in terms of PER increment independent of which AM is used.

FIG. 5: Comparison of Different Patterns of Dropping Frames assuming Copy (Regular and Random) and Interpolation through low-pass filtering (Upsample) method of replacement.

C. Hypothesis 2: Dropping Frames with Regards to Landmarks

At the beginning of this section, we conduct experiments to test hypothesis 2 directly. The focus is to subject the ASR decoding process to frames missing acoustic likelihood and see how the decoding error rate changes accordingly. Obviously we are interested in using landmark as a heuristic to choose the frames to keep or drop. To quantify if the information kept or discard is relatively important or not, dropping strategies (Landmark-keep and Landmark-drop) to two non-landmark-based strategies Random. Notice the Regular
strategy has been shown to be more effective than Random (e.g., in Fig. 5), however, to make the PER result of good indication, same amount of frames have to be dropped across different pattern. When we keep only landmarks (Landmark-keep) or drop only landmarks (Landmark-drop), the percentage of frames dropped can not be precisely controlled by the system designer: it is possible to adjust the number of frames retained at each landmark (thus changing the drop rate), but it is not possible to change the number of landmarks in a given speech sample, therefore precisely adjusting the drop rate to meet a different pattern is not practical. Depending on the test set selected, portion of frames containing landmark range from 18.5% to 20.5%. As oppose to Random, Regular does not provide flexibility on selecting dropping rate to match the landmark ratio exactly. Therefore, it is not covered in the first 2 experiments. However, in the 3rd experiment, we will compare a frame dropping strategy using landmark as heuristic against Regular dropping. But that experiment will serve a slightly different purpose.

As in the over-weighting experiment, two types of frame replacement are tested. The Fill\_0 strategy is an exact implementation of hypothesis 2: when frames are dropped, they are replaced by the least informative possible replacement (a log probability of zero). Figure 4 showed, however, that the Copy strategy is more effective in practice than the Fill\_0 strategy, therefore these two strategies are tested using a landmark-based frame drop pattern. Figure 4 showed that the Fill\_const strategy returns almost identical results to Fill\_0, so it is not separately tested here.

Experiment results are presented for both the TIMIT default test split, and for cross-validation (CV) using the whole corpus. The baseline implementation is directed from Kaldi. Since no frames are dropped, it returns the lowest PER. However, likelihood scoring for the baseline AM will require more computation when compared to a system which drops frame. For CV we report the mean relative PER increment ($\Delta$PER = 100 × (modified PER – baseline PER)/(baseline PER)), with its standard deviation in parentheses, across all folds of CV. Every matching pair of frame-drop systems (Landmark-keep versus Random) is tested using a two-sample $t$-test (Cressie and Whitford, 1986), across folds of the CV, in order to determine whether the two PER increments differ. If the two increments differ, then the lower of the two is marked with either * ($p < 0.05$) or ** ($p < 0.001$).
1. Keeping or Dropping the Landmark Frames

Table II illustrates the changes in PER increment that result from a Landmark-keep strategy (score only landmark frames) versus a Random frame-drop strategy set to retain the same percentage of frames. For each test set, we count the landmark frames separately and match the drop rate exactly between the Landmark and Random strategy. In all cases, the Landmark-keep strategy has a lower PER increment. Wilcoxon test has been conducted on the default test set, the test conclude the difference between all but the DNN Fill0 pair to be significant.

**TABLE II: PER increments for scoring Landmark frames only compared to randomly dropping similar portion of frames (CV stands for cross validation)**

| Acoustic model | Test regime | GMM | DNN |
|----------------|-------------|-----|-----|
|                | Default     | CV Mean (Stdev) | Default | CV Mean (Stdev) |
| **Metric**     | PER (%)     | PER Inc (%)    | PER (%) | PER Inc (%)    | PER (%) | PER Inc (%) |
| Baseline       | 23.8        | 0.0            | 22.8    | 0.0            | 22.7    | 0.0          |
| Fill0          | Landmark-keep | 36.1      | 51.7 | 33.4 | 46.5 (1.34)** | 49.6 | 118.5 | 49.7 | 139 (10.3)* |
| Random         | 42.3        | 77.7           | 42.1    | 84.6 (8.35)   | 50.9    | 124.2        | 52.8 | 154 (14.8) |
| Copy           | Landmark-keep | 35.2      | 47.7 | 32.3 | 41.5 (1.08)** | 29.4 | 29.3 | 26.9 | 29.3 (0.653)** |
| Random         | 44.0        | 84.9           | 44.1    | 93.5 (0.734)  | 38.4    | 69.3          | 37.6 | 80.9 (0.942) |

For the next experiment we inverted the setup: instead of keeping only landmark frames, we drop only landmark frames (call this the Landmark-drop strategy). Table III compares the PER increment of a Landmark-drop strategy to the increment suffered by a Random frame drop strategy with the same percentage of lost frames. The Landmark-drop strategy always return higher PER. However, only for the GMM setup Copy did we obtain a significant $p$ value during cross validation. The $p$ values for other setups range from 0.13 to 0.17. Again, Wilcoxon test has been conducted on the default test set, the test conclude only the GMM Copy pair demonstrated significant difference.

Through Table II and Table III we can conclude, when compared against a random strategy, dropping similar percentage of frames during the scoring process, it is preferable to avoid dropping the landmark. On the other hand, dropping the landmark may result in a more significant degradation of the accuracy. This supports the assumption that frames containing landmarks are indeed more important than others.
TABLE III: PER increments for dropping Landmark frames during scoring compared to randomly dropping a similar portion of frames (CV stands for cross validation)

| Acoustic model | GMM | DNN |
|----------------|-----|-----|
| Test regime    | Default | CV Mean (Stdev) | Default | CV Mean (Stdev) |
| Metric         | PER (%) | PER Inc (%) | PER (%) | PER Inc (%) | PER (%) | PER Inc (%) | PER (%) | PER Inc (%) |
| Baseline       | 23.8 | 0.0 | 22.8 | 0.0 | 22.7 | 0.0 | 20.8 | 0.0 |
| Fill0          | 25.6 | 7.56 | 24.0 | 5.33(1.36) | 24.2 | 6.61 | 23.1 | 11.1(1.58) |
| Random         | 24.1 | 1.26 | 23.4 | 2.68(1.23) | 23.6 | 3.96 | 22.4 | 7.53(1.24) |
| Copy           | 25.6 | 7.5 | 24.1 | 5.83(0.873)* | 24.3 | 7.1 | 22.1 | 6.44(0.836) |
| Random         | 24.6 | 3.3 | 23.1 | 1.14 (0.948) | 23.6 | 4.0 | 21.6 | 3.85(0.760) |

2. Using Landmark as a Heuristic to Achieve Computation Reduction

Methods in Table II and III compared the Landmark-keep, Landmark-drop, and Random frame drop strategies. Table IV illustrates PER increment (%) for the Landmark-keep and Regular frame-dropping strategies. In this experiment, we are no longer directly testing Hypothesis 2. Instead, we are trying to achieve high frame dropping rate subject to low PER increment. As dropped frames need not be calculated during the acoustic model scoring procedure, high dropping ratio can benefit the ASR by reducing computational load. The strategy leveraging landmark information is a hybrid strategy, on top of a standard Regular strategy, it keeps all landmark frames and over-weight the likelihoods of these frame as in VIA. For each acoustic model type (GMM vs. DNN), two different percentage rates of frame dropping are exemplified. In each case, we select a Regular strategy with high dropping rate, measure the percentage of frames dropped by the resulting frame-drop strategy after considering landmark frames, then devise a Regular only frame-drop strategy with a similar drop rate. Three different Regular drop rates are tested in Table IV: 33.3% (one out of three frames dropped, uniformly), 50% (one out of two frames dropped), and 66.7% (two out of three frames dropped). We highlighted results for one of the setup in bold as it achieves a very good trade off between high dropping ratio and low PER increment.
TABLE IV: *PER increments comparison between Landmark-keeping and Regular dropping strategy for GMM and DNN.*

| Copy | Default | Cross Validation | | | | | | | |
|------|---------|------------------|---|---|---|---|---|
|      | Drop Rate% | PER Inc% | Drop Rate% | PER Inc% | Inc STD% | Inc pVal | | | |
| Land | 41.0 | 1.26 | 44.4 | 1.84 | 0.0133 | 0.962 | | | |
| Reg  | 33.3 | 3.78 | 33.3 | 1.81 | 0.0119 | | | | |
| Land | 64.3 | 12.1 | 65.0 | 8.10 | 0.0182 | 0.159 | | | |
| Reg  | 66.7 | 10.1 | 66.7 | 6.91 | 0.0181 | | | | |
| Land | 58.8 | 0.44 | 58.4 | 1.90 | 0.167 | 0.0029 | | | |
| Reg  | 50 | 2.21 | 50 | 4.12 | 0.0115 | | | | |
| Land | 64.2 | 3.08 | 69.0 | 5.86 | 0.0121 | 0.0391 | | | |
| Reg  | 66.7 | 6.17 | 66.7 | 7.04 | 0.016 | | | | |

VII. DISCUSSION

Results in VI A tend to support hypothesis 1. However, the tendency is not statistically significant. The tendency is consistent for the GMM-based system, for all over-weighting factors between 1.0 and 3.0. Similar tendencies appeared for over-weight factors between 3.0 and 5.0 for DNN-based system.

Experiments in Section VI B tested different non-landmark-based frame drop strategies, and different methods of frame replacement. It was shown that, among the several strategies tested, the *Regular-Copy* strategy obtains the smallest PER. There is an interesting synergy between the frame-drop strategy and the frame-replacement strategy, in that the PER of a 50% *Regular-Copy* system (one out of every two frames dropped) is even better than that of a 33% *Regular-Copy* system (one out of every three frames dropped). This result, although surprising, confirms a similar finding reported by Sak *et al.* (2014). We suspect that the reason may be relevant to the predictability of a 50% drop rate, which smoothed out the cost in the lattice and created an effect similar to decoding with the frame-update rate at 20 ms instead of 10 ms.

It is worth mentioning that our definition of acoustic landmarks differs with Lulich (2010) – specifically, Lulich claims that there is no landmark in the center of Vowel and Glide; instead, formant-subglottal resonance crossing, which is known to sit between boundary of [-Vowel] and [+Vowel] contains a landmark. It is possible that an alternative definition of landmarks might lead to better results.

We can also observe that GMM and DNN acoustic models tend to perform differently
in the same setup. For example, for GMM, randomly dropping results in a higher PER than up-sampling, while it is not the same for the DNN models. Results also demonstrate that DNN models perform quite well when frames are missing. A PER increment of only 6% is achieved by throwing away 2/3 of the frames. GMM models tend to do much worse, especially when the drop rate goes up.

The best strategy appears to be to avoid dropping landmarks in almost every case we tested. Scoring only the landmark frames (the Landmark-keep strategy) out-performs both Random and Regular frame-drop-strategies. On the other hand, if landmark frames are dropped (the Landmark-drop strategy), we obtain higher PER when compared to randomly scoring a similar number of frames.

We find, therefore, that landmark frames contain information that is more useful to ASR than other frames. For example with a DNN, it is possible to drop more than 58% of the frames but only observe a 0.44% (PER increases from 22.7 to 22.8) increment in the PER compared to baseline. We could conclude that experiments support hypothesis 2 with statistical confidence.

Different drop rates are necessary for GMM and DNN in order to achieve the best trade off. For DNN, around 58% is ideal since there is almost no accuracy loss by chopping out more than half of the computation. Yet we have shown that the Landmark-keep DNN still significantly outperforms Regular-Copy up to drop rates as high as 69%. Overall, the Landmark-keep strategy performs better on DNN than GMM.

A. How Landmarks Affect the Decoding Results

Apart from the findings on changes in PER, we also looked into more detail on the effect of frame dropping based on landmarks. To be specific, we were interested in how throwing away other frames and only scoring the landmark frames will alter the insertion, deletion and confusion among phones. We compared the phone confusion matrices when we only scored the landmark frames, as compared to the timit/s5 GMM and DNN baseline described in Section V. Fig. 6 compares the insertion and deletion count between the 2 setups. The numbers reported in the figure are normalized error increment. They are calculated using error increment divided by the occurrence of each kind of phone. We use this measure to reflect the increment ratio while avoiding having to deal with situations that could lead to
division by zero.

FIG. 6: The normalized error increment for a) insertion errors and b) deletion errors (y-axis represent different manners of articulators and x-axis represent different systems)

Overall, dropping frames introduces minor reduction to the phone insertion rate, while the phone deletion rate significantly worsens. We suspect that after dropping frames, the decode is less effective at capturing transitions between phones, resulting in correctly detected phones spanning over other phones. In Figure 6b we can see that the Landmark-keep strategy is more effective than the Random strategy, since it returns a lower deletion rate increment. We believe this is because the landmark contains sufficient acoustic information about each phone to force it to be recognized. However, we do not know why landmarks are less effective with DNN when compared to GMM on reducing phone deletion. A possible reason might be that more frames were stacked together in the splicing process for the DNN than for the GMM (Veselý et al. 2013), and as a result, the DNN may be more likely than the GMM to misclassify a landmark as one of the context phones rather than as the phone correctly associated with the landmark. If we do consider providing landmarks as extra information to ASR, in order to reduce computation load for example, the difference across GMM and DNN models should be considered.
VIII. CONCLUSIONS

Phones can be categorized using binary distinctive features, which can be extracted through acoustic cues anchored at acoustic landmarks in the speech utterance. In this work, we proved through experiments for both GMM- and DNN-based ASR systems operating on MFCC features, on the TIMIT corpus, using both the default and cross validation train-test-split, that frames containing landmarks are more informative than others. We proved that paying extra attention to these frames can potentially improve ASR accuracy, or compensate for accuracy lost when dropping frames during Acoustic Model likelihood scoring. We leveraged the help of landmarks as a heuristic to guide frame dropping during speech recognition. In one setup, we dropped more than 58% of the frames while adding only 0.44% to the Phone Error Rate. This demonstrates the potential of landmarks for computational reduction for ASR systems. We conclude that frames containing acoustic landmarks provide more information to a conventional GMM or DNN ASR than other frames.
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