Corpus-based Noisy Harmonic Grammar modeling of word-medial /t/-flapping in American English[*]

Cheonkam Jeong **Sung-Hoon Hong**[**]
(Hankuk University of Foreign Studies)

Jeong, Cheonkam and Sung-Hoon Hong. 2017. Noisy Harmonic Grammar modeling of flapping in American English based on a statistical analysis. *Studies in Phonetics, Phonology and Morphology* 23.1. 117-143. This paper investigates the gradient aspect of flapping in American English, considering both the language internal factors *stress* and *morphological complexity* and the language external factor *lexical frequency*. To reflect the gradient aspect of flapping, flapping rates were regarded as dependent variables, and a statistical analysis was conducted with both language-internal and language-external factors. Due to the range of dependent variables [0, 1], a zero/one inflated beta regression was conducted. The results verified that the more frequent a carrier word containing a word-medial /t/ is, the more likely it is for the word-medial /t/ to be realized as a flap, and that the word-medial /t/ in a morphologically simple word is more likely to be realized as a flap than one in a morphologically complex word. Thereafter, Noisy Harmonic Grammar analyses were performed, and the extended version showed an improvement over the original model of 83.228%. **(Hankuk University of Foreign Studies)**

Keywords: flapping, frequency, Noisy Harmonic Grammar, corpus, Buckeye, zero/one inflated beta regression

1. Introduction

It is well known that aspiration and flapping are allophonic alternations depending on stress and syllable structure of the voiceless alveolar stop in American English. The voiceless alveolar stop is aspirated when it is in the onset of a stressed syllable (e.g. ə.ˈ[t^h]ɛnd), and the stop is realized as a flap when it is in the onset of an unstressed vowel or in non-foot initial position (e.g. ˈwɔ.[ɾ]ɚ) (Kiparsky 1979, Giegerich 1992,

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** Corresponding author

Inkelas 2014). However, these allophones are not always strictly distributed; rather, there are variations in their distribution. In this regard, this paper aims to examine the gradient aspect of flapping, or alternation between [tʰ] and [ɾ], in American English.

The goal of this paper is two-fold. The first goal is to make statistical modeling to attain quantitative evidence. For this, we will locate the word-medial voiceless consonants in a speech corpus, the Buckeye Speech Corpus (Pitt et al. 2007). Thereafter, a statistical analysis of them will be conducted, considering the effects of both the language-internal factor *morphological complexity* and the language-external factor *lexical frequency* on flapping in American English as Patterson and Connie (2001) did, as well as the effect of the conditioning factor *stress* Hong (2009) considered. The other goal is to provide a theoretical analysis. To do it, Noisy Harmonic Grammar (Pater et al. 2007, Pater 2009, Boersma and Pater 2013; henceforth, NHG) analyses will be adopted.

The organization of this paper is as follows. In section 2, we will review the factors that exert an influence on flapping in American English. In section 3, we will consider these factors to locate target words in the Buckeye Speech Corpus and conduct a statistical analysis. In section 4, we will present a NHG analysis of the variation in flapping, and then we will provide an extended-NHG analysis using the frequency effects model proposed by Coetzee and Kawahara (2013).

2. Factors affecting flapping in American English

In American English, flaps are allophones of the alveolar stops /t, d/. When a flap is produced, the tongue tip is first curled up and back in a retroflex gesture, and then it strikes the roof of the mouth in the post-alveolar region as it moves towards the passive articulator the lower front teeth (Turk 1992, Ladefoged 2006). It is widely acknowledged that stress is a conditioning factor for this phenomenon. Previously, Zue and Laferriere (1979) exhaustively described the six environments for the phonetic variants of word medial /t, d/, two of which they considered suitable for flapping: between a stressed vowel and an unstressed vowel (i.e. V_v) and between unstressed vowels (i.e. v_v). They also reported that between a stressed vowel and an unstressed vowel, flaps occur categorically whereas between unstressed vowels, they are optional. As far as this phenomenon is concerned, Hong (2009) compared the rate of flap production in post-stress environment with that between unstressed vowels using the Buckeye Speech Corpus and TIMIT (Garofolo et al.1993), and verified that between unstressed vowels flaps are gradient.

Moreover, following Patterson and Connie (2001), morphological complexity will be examined as another language-internal factor that affects flapping. Their study was motivated by Treiman et al. (1994), who found that children were highly likely to misspell /t/-driven flaps as voiced alveolar stops, since flaps are phonetically voiced. Interestingly, however, their experiments demonstrated that children were less likely to misspell /t/-driven flaps as voiced alveolar stops in morphologically complex words such as *cuter* than in morphologically simple words like *duty*. This shows that children use not only phonetic information but also morphological information to aid themselves in spelling out words. Based upon the findings of Treiman et al. (1994), Patterson and Connie (2001) contended that when a word-medial /t/ is in stem-final position, as in *concentrated*, it should be more likely to be realized as [t^h], which is analogous to children's spelling of flaps. In this sense, they hypothesized that the likelihood of a word-medial /t/ being realized as a flap should be lower in morphologically complex words than in morphologically simple ones. Indeed, their corpus-based research demonstrated the discrepancy between them (62.8% vs. 95.9%).

It is also known that the language-external factor lexical frequency exerts an influence on flapping. Patterson and Connie's (2001) corpus-based research demonstrated that in the post-stress environment, word-medial voiceless alveolar stops in frequent words were more likely to be realized as flaps than those in infrequent words (95.4% vs. 76.1%). Similarly, Hong (2009) verified that in the case of optional flapping, lexical frequency has a significant impact on flap production using two corpora. His corpus-based research showed that in the Buckeye Speech Corpus, the percent of flap production is 70.89% in low frequency carrier words and 86.82% in high frequency carrier words (χ^2=67.058, p<.001, df=1); in TIMIT, the percentage of flapping is 69.40% in low frequency words and 90.93% in high frequency words (χ^2=152.759, p<.001, df=1).

3. Statistical analysis of flapping in the Buckeye Speech Corpus

3.1 The data and research method

The Buckeye Speech Corpus (Pitt et al. 2007) was used as the primary data source for this paper, in which interviews of 40 native speakers from Ohio were recorded and then transcribed. The total number of word tokens is over 300,000, of which approximately 160,000 were phonetically transcribed. In the corpus, a flap is transcribed as *dx*. The transcription information provided in the corpus was assumed to reflect acoustic properties, and therefore flaps were judged based upon the transcribed forms.

Any word containing a medial /t/ was extracted and examined using *Praat* (Boersma and Weenink 2016, Version 6.0.18). As this paper aims to consider the alternation between [t^h] and [ɾ] in the contexts relevant to flapping, word medial voiceless alveolar stops realized as either [t^h] or [ɾ] were collected. Therefore, any word-medial voiceless alveolar stop realized as a sound other than [t^h] or [ɾ] was discarded[1]. Apropos of the distribution of word-medial /t/, four contexts were considered as shown in (1).

(1) The four contexts of word-medial /t/
   a. V(r)_v: between a stressed vowel and an unstressed vowel (e.g. *wáter*)
   b. v(r)_v: between two unstressed vowels (e.g. *actívity*)
   c. V(r)_V: between a primary stress and a secondary stress (e.g. *détàil*)
   d. v(r)_V: between an unstressed vowel and a stressed vowel (e.g. *atténtion*)

As illustrated in Table 1, of the total of 3568 tokens, 3153 tokens in the contexts of V(r)_v and v(r)_v were subject to flapping[2], and of these 3153 tokens, 2893 were realized as flaps (91.8%). In the contexts of V(r)_V and v(r)_V, all word-medial /t/s were realized as the aspirated allophone [t^h]. Since this paper examines the alternation between [t^h] and [ɾ] in two possible environments for flapping (i.e. post-stress (V(r)_v) and unstressed (v(r)_v)), we henceforth focus only on these two contexts.

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1 There were some alignment errors and transcription errors in the Buckeye Speech Corpus. We manually checked them and discarded 488 out of the total of 4,056 tokens, with the excluded tokens including word-medial voiceless alveolar stops being realized as some sound other than [t^h] or [ɾ].

2 Word-medial voiceless alveolar stops were investigated in the following contexts: V(r)_v and v(r)_v (on the condition for flapping, see Ladefoged (2006), Goldsmith (2011), and Kahn (1976)).

Table 1. The distribution of word-medial voiceless alveolar stops in the Buckeye Speech Corpus

Environment	Phones	Token No.	%
V(r)_v	t^h	111	4.39
	ɾ	2417	95.61
v(r)_v	t^h	149	23.84
	ɾ	476	76.16
V(r)_V	t^h	12	100.00
	ɾ	0	0.00
v(r)_V	t^h	403	100.00
	ɾ	0	0.00

(2=2136.3, p<.001, df=3)

3.2 Factors

3.2.1 Language-internal factors: stress and morphological complexity

As mentioned in the previous section, stress is regarded as a conditioning factor in this paper. Since the Buckeye Speech Corpus does not provide stress information, stress information was taken from *Merriam-Webster's Collegiate Dictionary* (11th edition), and both primary and secondary stress were regarded as conditioning factors. For instance, included in the examination were any medial /t/ following a secondary stress, as in the word types like *accumulated*, and any medial /t/ following a primary stress, as in word types such as *water*.

There were some word types that contain more than one voiceless alveolar stop. For such cases, the transcription information was manually checked. For instance, in the case of word types like *motivated*, the first /t/ and the second /t/ were both subject to flapping since they follow the primary stress and the secondary stress, respectively. In the Buckeye Speech Corpus, the frequency of the word type *motivated* is 5, and in each of these tokens, both of the word-medial alveolar stops are realized as flaps. In such cases, only the first /t/ after a primary stress was viewed as a flap, for flapping occurred in a word type, not in two word types.

As to morphological complexity, the data set was categorized into two groups, following Patterson and Connie (2001). The first group consists of morphologically simple words which contain morpheme-internal voiceless alveolar stops (e.g. beau[t][3]y). On the other hand, the second group is made up of morphologically complex words which contain a voiceless alveolar stop before a morpheme boundary (e.g. educa[t]ed)[4].

Since morphological complexity was difficult to judge in some forms, several measures had to be taken. First, when a voiceless alveolar stop belonged to a bound base (e.g. *veget*able(s), *theat*er, *monit*or, and *dat*a), the carrier word types were treated as morphologically simple, since bound bases cannot be used alone. Second, following Patterson and Connie (2001), the semantic relationship between base forms and derivatives was considered. For example, the word type *sweater* was regarded as morphologically simple since it is reportedly no longer related to the noun *sweat*. Lastly, the concept of stem extender was adopted. Word types such as *form-at-ive* and *affirm-at-ive* were treated as having a /t/ before a morpheme boundary since stem extenders expand the roots to form the stems *form-at* and *affirm-at*, respectively. Therefore, such word types were viewed as morphologically complex.

3.2.2 Language-external factor: lexical frequency

Since the size of the Buckeye Speech Corpus is small, the frequency information was taken from the Corpus of Contemporary American English (COCA; Davies 2008). Although word types were extracted, lemma frequencies were counted rather than type frequencies. This treatment was due to the possibility that frequency effects and morphological effects could have been highly correlated with each other, for the morphological complexity of a word type could have affected the frequency of the word type. For example, in the case of the word type *sweetest*, the type frequency of it is 1,017 whereas the lemma frequency of it is 32,649. This huge discrepancy between the two frequencies may be due to the effect of morphological complexity. Hence to examine both frequency effects and morphological effects, it seemed appropriate to use lemma frequencies rather than type frequencies.

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3 The brackets in the word types *beauty* and *educated* are used to mark the target phones, not to represent phonetic transcriptions.

4 As most suffixes attached to stems in the data are vowel-initial ones such as *-ing*, *-ed*, and *-er*, morphologically complex words are defined as having a word-medial /t/ before a morpheme boundary.

Moreover, so as not to distort the results, plural forms were incorporated into their base or singular forms. In the Buckeye Speech Corpus, there were many singular-plural pairs such as *ability* and *abilities*. As lemma frequencies were applied to word types, both word types were given the same lemma frequency of 60,491 in this case. If they had been treated differently, the results could have been distorted, for the word-medial /t/ in the word type *ability* occurs in the same context for flapping as the one in the word type *abilities*. In both cases vowels surround the word-medial /t/, and the location of stress in the two word types is also the same.

3.3 Statistical Analysis

3.3.1 Zero/One Inflated Beta Regression

In order to treat the gradient aspect of flapping, flapping rate (*dx*/*FBuckeye*) was regarded as the dependent variable (y_i), with this rate being defined as the frequency of a word type in which flapping (*dx*) occurs divided by the frequency of that word type (both with and without flapping) in the Buckeye Speech Corpus (*FBuckeye*). For instance, the frequency of the word type *pretty* in the corpus is 197, and in 190 of these tokens, word-medial voiceless alveolar stops are realized as flaps. Hence the flapping rate of *pretty* is 0.96, 190 (*dx*) /197 (*FBuckeye*).

Since the dependent variables are percentages, an appropriate statistical model is Beta Regression. Beta Regression is used when the dependent variables are numerical, percentages, or continuous proportions within the open interval (0, 1), and the distribution shapes of the dependent variables are left-skewed, right-skewed, “J,” inverted “J,” “U,” or uniform (Kieschnick and McCullough 2003, Ospina and Ferrari 2012). However, since the data size was small, there were a large number of words with frequency values of 1. In these cases, if the word-medial /t/ is realized as a flap, then the flapping rate is 1 (100%), and if not, then the flapping rate is 0 (0%)[5]. This makes the distribution shape “inflated” at the values of 0 and 1, as illustrated in

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[5] For example, the frequency in the Buckeye Speech Corpus of the word type *highlighted* is 1, and its word-medial /t/ is realized as a flap, which makes its flapping rate 1 (100%). On the other hand, the word-medial /t/ in the word type *located*, whose frequency in the Buckeye Speech Corpus is 1, is realized as an aspirated stop, so the flapping rate in this case is 0 (0%). Including these cases, out of 441 total word types, the flapping rate of 333 word types is 1 (100%) and that of 35 word types is 0 (0%)

Figure 1. Hence a statistical model to accommodate these inflated values of 0 and 1 had to be found, and the appropriate statistical model is Zero/One Inflated Beta Regression (henceforth, ZOIB).

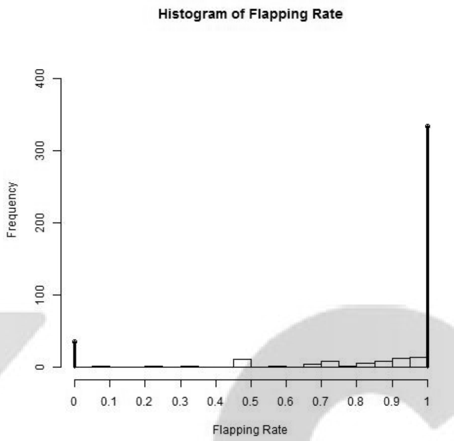

Figure 1. The histogram of flapping rate in the Buckeye Speech Corpus

ZOIB is affiliated with beta regression. The only difference between ZOIB and beta regression is the range of values. In ZOIB, values are within the closed interval [0, 1], while in beta regression, values are within the open interval (0, 1). The principles of ZOIB are as follows. First, ZOIB distinguishes zero values (y_i=0) from non-zero values (0<y_i≤1), for there is a qualitative difference between them. To be specific, a word-medial /t/ that is never realized as a flap is qualitatively different from word-medial /t/s that are always or sometimes realized as flaps. Similarly, there is another process that distinguishes one values (y_i=1) from non-one values (0≤y_i<1). By the same logic as the first process, a word-medial /t/ that is always realized as a flap is qualitatively different from medial stops that are sometimes or never realized as flaps. Therefore, in ZOIB model, a beta regression is applied to the interval of 0<y_i<1, which deals with the gradient aspect. Logistic regressions are applied to the others, which accommodate categorical results (y_i=0 or y_i=1), respectively.

3.3.2 Model Fitting

To treat the gradient aspect of flapping, flapping rates (*dx*/*FBuckeye*) were regarded as the dependent variables (y_i). The independent variables were stress (β_{str}), lexical frequency (β_{lf}), and morphological complexity (β_{mc}). The values of the independent variable stress (β_{str}) were categorically coded. When a word-medial /t/ occurred in the post-stress environment it was coded as 1, while a word-medial /t/ occurring between unstressed vowels was coded as 0. The values of the independent variable morphological complexity (β_{mc}) were coded in the same way. When a word-medial /t/ was morpheme-internal it was coded as 1, whereas a word-medial /t/ occurring before a morpheme-boundary was coded as 0. The independent variable lexical frequency was transformed into a base *e* logarithm.

The formulae in which all factors were considered were as follows.

(2)
$$logit\left(\mu_i^{(0,1)}\right) = \beta_{itc} + \beta_{lf}\, log(ith\ \ lexical\ \ frequency) \\ + \beta_{mc} ith\ \ internal + \beta_{str} ith\ \ post\ \ stress$$

(3)
$$log(v_i) = \beta_{be} 1/ith\ \ Fbuckeye$$

(4)
$$logit(p_i) = \beta_0$$

(5)
$$logit(q_i) = \beta_1$$

When the values of dependent variables, or flapping rates, were within the open interval (0, 1), which dealt with the degree to which the independent variables exerted an influence on the dependent variables, beta regression was applied as in (2). When the values of dependent variables were 0 or 1, logistic regression was applied, respectively, as in (4) and (5). However, that the values of the dependent variables were 0 or 1 meant that flaps were categorically realized. Therefore, the estimated coefficients p_i and q_i in (4) and (5) were coefficients of constants like the values of intercepts.

On the one hand, the variance of the dependent variable *dx/FBuckeye* (flapping rate) was affected by *FBuckeye*, or frequency in the Buckeye Speech Corpus. That is, *FBuckeye* was proportional to variance. For instance, the Buckeye frequency (*FBuckeye*) of the word type *putting* was 12, 11 of which were realized as flaps, hence the dependent variable of it, 0.92. On the other hand, the Buckeye frequency of the word type *potty* was 1, and the only one medial /t/ was realized as a flap, therefore the dependent variable of it, 1. This violated the homogeneous variance assumption. Fortunately, it was possible to solve the problem in ZOIB model via a log function, and it was applied to the value of *FBuckeye*, as in (3).

As mentioned in the previous section, ZOIB is a mixed model in which different functions are adopted depending on the ranges of the dependent variables. It is thus almost impossible to calculate coefficients in the same way as in other linear regression models such as simple or multiple linear regression models. Therefore, in ZOIB, coefficients are estimated by Bayesian inference[6] and by using posterior samples generated with the Markov Chain Monte Carlo sampling technique.

In order to estimate coefficients in formulae (2), (3), (4) and (5), ZOIB analysis on the data was performed using the **zoib** package (Liu and Kong 2015) in R (version 3.3.1). The first step in estimating coefficients was to obtain posterior samples, which were generated with the Markov Chain Monte Carlo sampling technique. For this, 5000 simulations were done (2 chains, 5000 iterations, burn-in periods=200, and thinning period = 2). The next step was to interpret coefficients estimated from posterior samples. For this, 0.1 was set as the significance level of α,[7] since the data size was small (441 types), and the data was not obtained from an experiment under strict control, but rather from observation. Although this treatment can be challenged, it is not a groundless one. Eddington (2015) argued that the cut-off point of .05 established by the statistician Fisher is completely arbitrary, following Kline (2004), who strongly criticized the cut-off point as follows[8]:

> "Consider the choice of .05. There is no real reason it is better than any other cutoff point. It was a completely arbitrary point set by Fisher. In fact, there are

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[6] For further statistical information on ZOIB, see Liu and Kong (2015).

[7] When the α level was set at 0.05, all factors showed overall practical significance, but morphological complexity did not show strict statistical significance.

[8] Baayen (2008) also indicated that it is controversial to set a standard α level because the p-value can vary depending on the field of research. He stated that in experimental fields such as physics, the p-value can be very small because strict experimental settings are not difficult to design. However, in some fields such as social science small p-values are hard to obtain, for it is very hard to control other factors.

some reasons why it would make more sense if it were .1 in the behavioral sciences instead of .05 (Kline 2004, as cited in Eddington 2015, p.19)"

The coefficients estimated via posterior samples were as follows.

Table 2. Distribution of posterior samples

Parameter	Mean	5% quantile	95% quantile
β_{be}	1.644	1.37	1.911
β_1	1.523	1.312	1.739
β_0	-2.464	-2.773	-2.18
β_{str}	0.754	0.375	1.122
β_{mc}	0.418	0.042	0.789
β_{lf}	0.246	0.131	0.359
β_{itc}[9]	-2.071	-3.229	-0.879

The values in Table 2 referred to regression coefficients. They were the means of parameter values estimated by Bayesian inference with posterior samples. With the estimated coefficients, the formula to calculate flapping rates (y_{fr}) in the open interval (0, 1) can be made as follows: $y_{fr} = logit^{-1}(-2.072 + 0.246 *$ the lexical frequency of a target word + 0.752 + 0.418). As mentioned above, β_0 and β_1 denoted the coefficients when the values dependent variables 0 and 1, respectively. In other words, they were not under the effects of the independent variables, so that it was more plausible for the values of β_0 and β_1 to be regarded as constants like intercepts.

9 β_{itc} refers to intercept.

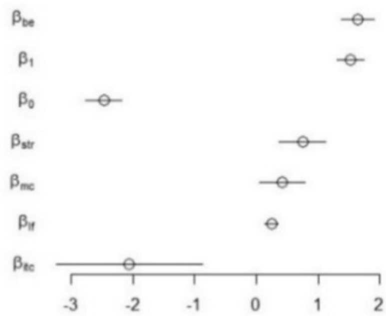

Figure 2. 90% credible interval for beta

As illustrated in Table 2 and Figure 2, the three factors β_{str}, β_{mc}, and β_{lf} had impacts on flapping, in that none of the coefficients β_{str}, β_{mc}, or β_{lf} had values of 0.[10] Therefore, it is concluded that as Hong (2009) verified, word-medial voiceless alveolar stops are more likely to be realized as flaps in the post-stress environment than between unstressed vowels. Additionally, as Patterson and Connie (2001) argued, morpheme-internal voiceless alveolar stops are more likely to be realized as flaps than those occurring before morpheme boundaries. Finally, the more frequent the carrier words are, the more likely their medial voiceless alveolar stops are to be realized as flaps, which is in agreement with both Patterson and Connie (2001) and Hong (2009).

4. A Noisy Harmonic Grammar analysis of flapping

4.1 Noisy Harmonic Grammar (NHG)

Like Optimality Theory (Prince and Smolensky 1993/2004; henceforth, OT), Harmonic Grammar (Legendre et al. 1990, Smolensky and Legendre 2006, Potts et al. 2010) is a constraint-based grammar. However, the main difference between OT and HG is that in the former, the optimal candidate is determined by constraint weights, whereas in the latter, it is determined by constraint rankings. This difference is illustrated below in tableaux (6).

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[10] If estimated coefficients include 0, the relationship between factors and the dependent variables is statistically insignificant in ZOIB model.

(6) The difference between OT and Harmonic Grammar

a. Optimality Theory: DEP >> *COMPLEX >> MAX

/lʊst/	DEP	*COMPLEX	MAX
lʊst		*!	
☞lʊs			*
lʊs.ti	*!		

b. Harmonic Grammar: w(DEP) > w(*COMPLEX) > w(MAX)

/lʊst/	5 DEP	1.5 *COMPLEX	1 MAX	**H**
lʊst		-1		-1.5
☞lʊs			-1	-1
lʊs.ti	-1			-5

As illustrated in the tableaux (6), the optimal candidate was drawn by ranking values in OT, while in HG it was drawn by harmonic score (**H**), which is the sum of the products of the weight of each constraint and the number of violations marked as negative numbers. However, one problem with Harmonic Grammar is that it cannot or account for variation. Therefore, NHG, Harmonic Grammar with noise, will be used to analyze the variation of flapping in this paper.

NHG is similar to Stochastic OT (Boersma 1997, Boersma and Hayes 2001, Hayes and Londe 2006) in its way of dealing with variation. The major difference between them is that Stochastic OT assumes strict domination, as in the original model of OT. Therefore, a candidate that violates a more highly ranked constraint is totally excluded. On the other hand, as the optimal candidate is selected by weight in NHG, even a candidate that violates the most heavily weighted constraint can still be optimal, as shown in tableaux (7) below.

(7)

	Con1 w=75	Con2 w=53	Con3 w=51	**H**
cand1		-1	-1	-104
☞cand2	-1			-75

	Con1 w=75	Con2 w=53	**H**
cand1		-2	-106
☞cand2	-1		-75

In the first tableau, although the second candidate violated the most highly ranked constraint, *constraint 1*, it was evaluated as an optimal candidate. This is because the harmonic score (**H**) of the second candidate (75*(−1) = −75) is higher than that of the first candidate (53*(−1) + 51*(−1) = −104). Likewise, in the second tableau, the second candidate is chosen as the optimal one, for its harmonic score (**H**) (75*(−1) = −75) is higher than that of the first one (53*(−2) = −106).

4.2 Noisy Harmonic Grammar analysis of flapping

Several steps were taken to perform a NHG analysis on flapping, the first of which was to determine the relevant constraints. As demonstrated in Table 1 of section 3, word-medial /t/ is realized as [t^h] when followed by a stressed vowel (see also Eddington and Elzinga 2008). Therefore, two markedness constraints can be established: *Vt^hv and *vt^hv. In addition, based on Trieman et al. (1994), if a voiceless alveolar stop occurs before a morpheme boundary, it is more likely to be realized as [t^h] than as [ɾ]. Hence the markedness constraint * ɾ$]_{Mor}$ can also be made[11,12]. Lastly, the faithfulness constraint IDENT-AS is proposed.

(8) The four constraints for flapping

a. *Vt^hv

The aspirated stop [t^h] should not occur between a stressed vowel and an unstressed vowel.

b. *vt^hv

The aspirated stop [t^h] should not occur between two unstressed vowels.

c. *ɾ$]_{Mor}$

The flap [ɾ] may not occur before a morpheme-boundary

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11 This tendency may also be concerned with the inhibiting function of boundaries proposed by Kenstowicz and Kisseberth (1977). According to them, there are two functions of boundaries: an inhibiting function and a conditioning function. Of the two, the first function might be helpful to establish the markedness constraint *ɾ$]_{Mor}$, based on phonological accounts. However, the data set is not enough to make such a generalization that morpheme boundaries prevent flapping being applied across them. Therefore, the markedness constraint * ɾ$]_{Mor}$ is established, only based on Trieman et al. (1994).

12 An anonymous reviewer pointed out that the morphological boundary effect could be addressed by employing the concept of base the identity (Benua 1995, Kenstowicz 1996). If we follow this idea, the boundary effect could be handled by Ident-BA (base, affixed word) dominating the markedness constraints, which in turn outrank Ident-IO (input, output).

d. IDENT-AS
Corresponding alveolar stops (AS) in input and output have identical feature composition.

The next step of the NHG analysis was to determine the constraint weights. To obtain these weights, an initial grammar was needed in which constraints were given initial weights of 50 for faithfulness constraints and 100 for markedness constraints (Coetzee and Pater 2011). The pair distribution information was also needed. For this, the data were assorted, based upon four combinations as shown in Table 3. The column labeled as Observation % in Table 3 contains the observed pair distribution information for each type of environment.

Table 3. The distribution of the realization of word-medial voiceless alveolar stops in the Buckeye Speech Corpus

Environment	Phones	Token No.	Observed %
Post-stress & Morpheme-internal	t^h	63	3.85
	ɾ	1575	96.15
Post-stress & Morpheme-boundary	t^h	48	5.39
	ɾ	842	94.61
Unstressed-medial & Morpheme-internal	t^h	102	20.90
	ɾ	386	79.10
Unstressed-medial & morpheme-boundary	t^h	47	34.31
	ɾ	90	65.69

An OT script containing both the initial weights of the constraints and the pair distribution information was presented to *Praat*. The constraint ranking values were then learned by NHG learning[13] as presented in (9). Next, the OT script was revised with the learned constraint weights and submitted to *Praat*, and a predicted distribution was made as in Table 4.

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13 For this, the "Linear OT" strategy was adopted, and all other settings were kept at the *Praat* default settings. The default settings were as follows: (i) the initial weights of constraints were 50 for faithfulness constraints and 100 for markedness constraints; (ii) the evaluation noise of was 2.0; and (iii) the initial plasticity was set at 1.0, with 4 decrements of 0.1 at every 100,000 replications.

(9) The learned constraint weights of flapping

$*Vt^hv$	86.278
$*vt^hv$	82.933
$*ɾ]_{Mor}$	0.131
IDENT-AS	80.789

To demonstrate the validity of these results, the predicted flapping rate via the learned grammar was compared with the observed flapping rate. The results of this comparison are shown in Table 4.

Table 4. Comparison between observed and predicted flapping rates

Environment	Observed flapping rates	Predicted flapping rates
Post-stress & Morpheme-internal	96.43%	97.48%
Post-stress & Morpheme-boundary	91.44%	93.08%
Unstressed-medial & Morpheme-internal	78.68%	77.65%
Unstressed-medial & Morpheme-boundary	67.84%	66.43%

A correlation test revealed that there was a close relationship between observed flapping rates and predicted flapping rates (r=0.999, p<.001), indicating that the NHG analysis was successful.

4.3. Frequency effects modeling

To begin with, a linear regression analysis between frequency and flapping rates[14] was conducted in order to confirm that doing frequency effects modeling was an acceptable method of analysis for flapping. The independent variable was log-

[14] Note that this statistical analysis was done only to see the overall relationship between frequency and flapping rates. Therefore, the values of 0 and 1 were deleted in this statistical analysis, for they were categorical.

transformed COCA frequency (base *e*), and the dependent variable was flapping rate in the Buckeye Speech Corpus.

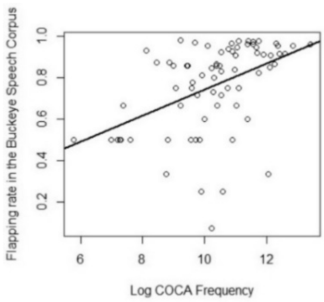

Figure 3. The linear regression between frequency and flapping rate

In Figure 3, the statistical result show that there is a linear relationship between frequency and flapping rate (adjusted R^2=0.197, p<.001). Therefore, a NHG analysis with frequency effects modeling is appropriate for flapping.

Coetzee and Kawahara (2013) explained in detail how the language-external factor frequency is encoded in NHG. The weights of faithfulness constraints can be adjusted in accordance with frequency. To be specific, the weights of faithfulness constraints can be raised for infrequent words or lowered for frequent words by adjusted scaling factors (*sf*). The extent of these adjustments is determined by a probabilistic distribution function known as the beta distribution function.

The beta distribution is a continuous probability distribution within the interval (-ρ, ρ)[15], and its shape is determined by two shape parameters α and β. When α > β, the distribution is left-skewed; when α < β, it is right-skewed. In Coetzee and Kawahara (2013), the mean or median log frequency was set as α, and the log frequency of a specific word was referred to as β. In addition, the mode value of each bin within the interval (-ρ, ρ) was regarded as a scaling factor, which would be added to the faithfulness constraint weights. Therefore, in the cases of infrequent words (α > β), the faithfulness constraint weights are raised, since the values of scaling factors have positive values and then are combined with the faithfulness constraint weights. On the other hand, for frequent words (α < β), the faithfulness constraint weights are

15 For further information of the formula, see Coetzee and Kawahara (2013).

lowered because the scaling factors have negative values and are added to the faithfulness constraint weights.

4.4 Frequency effects modeling for flapping

The first step toward frequency effects modeling was to make bins. For this, the fourth context from Table 4, Unstressed-medial & Morpheme-boundary (henceforth, UnstBdry), was chosen as the target group. Since the average of the observed flapping rates in the fourth context (UnstBdry) was the lowest when only language-internal factors were considered, it was deemed likely that this context would clearly demonstrate the frequency effect. Thereafter, the median frequency 8.6 in this group was regarded as the reference frequency α, and considering it, three bins were made to accommodate 48 word types which belonged to this group. Each bin was expected to accommodate 16 word types[16]. However, the number of tokens whose frequency was 9.6 was 4, so that the second bin came to accommodate 18 word types, as shown in Table 5.

Table 5. Frequency bins for the fourth context (UnstBdry)

Frequency ranges	Frequency bins	The number of word types	Observed flapping rates
4.6-7.5	7.5	16	63.54
7.7-9.6	9.6	18	66.67
9.8-10.9	10.9	14	74.25

The second step was to calculate the values of scaling factors. To do this, the three shape variables α, β, and the interval parameter ρ were needed. As mentioned above, α was the reference frequency, which was set as 8.6 in this context, while β stood for the frequency value of each bin. For each interval parameter ρ, mode values that

[16] Coetzee and Kawahara (2013) argued that the more the frequency bin was and the more the tokens per bin were, the more accurate the prediction would be. In this regard, they proposed that each bin should contain at least 50 tokens. However, such standard could not be applied to the data in this paper, for flapping rates of word types rather than tokens were examined. Therefore, considering the reference frequency 8.6 in the fourth context, three bins each containing at least 14 word types were made.

stood for scaling factors were obtained by using the beta distribution function. The results are presented in Table 6 below.

Table 6. Scaling factors for flapping in the fourth context (UnstBdry)

		Baseline	ρ=2	ρ=3	ρ=4	ρ=5	ρ=6	
Frequency bins	7.5	0	0.14	0.23	0.31	0.39	0.47	Scaling factors
	9.6	0	-0.12	-0.19	-0.25	-0.31	-0.37	
	10.9	0	-0.26	-0.39	-0.53	-0.66	-0.79	

As can be seen in Table 6, the greater the value of the interval parameter ρ was, the greater the absolute mode values, or the scaling factors, were. This means that a higher frequency effect was expected. Whether the mode values were negative or positive denoted direction. Faithfulness constraint weights were adjusted with these different scaling factors. One example, in which the interval parameter ρ=4, is illustrated as follows.

Table 7. Sample adjustment of faithfulness constraint weights when ρ=4

		sf	*Vtʰv	IDENT-AS	*vtʰv	*ɾ]$_{Mor}$
		0	86.28	80.789	82.93	0.131
Frequency bins	7.5	0.31	86.28	81.099	82.93	0.131
	9.6	-0.25	86.28	80.539	82.93	0.131
	10.9	-0.53	86.28	80.259	82.93	0.131

In Table 7, as predicted above, in the case of 7.5, the weight of the faithfulness constraint IDENT-AS was raised from 80.789 to 81.099. On the other hand, in the cases of 9.6 and 10.9, the weights were lowered from 80.789 to 80.539 and 80.259, respectively.

The third step was to predict flapping rates. To do it, 15 OT scripts[17] reflecting adjusted faithfulness constraint values at different ρ values were made and then

[17] One sample script, in which case the frequency value was 7.5 when the interval parameter ρ=4, was attached to this paper (Appendix B).

submitted to *Praat*. As a result, the distributions per ρ value shown in Table 8 were obtained.

Table 8. Predicted flapping rates

		Baseline	ρ=2	ρ=3	ρ=4	ρ=5	ρ=6
Frequency bins	7.5	66.43	65.123	63.73	63.012	61.783	61.019
	9.6	66.43	68.005	68.758	69.626	69.925	70.922
	10.9	66.43	69.778	71.144	72.622	74.033	75.111

As seen in Table 8, without the effects of scaling factors, the uniform flapping rate 66.43 was predicted. On the other hand, different flapping rates were predicted depending on different frequency bins, and the extent of the differences varied depending on the interval parameter ρ.

The last step was to choose the most proper interval parameter that modeled predicted flapping rates closest to observed flapping rates. For this, the mean square error (MSE) was calculated, following Coetzee and Kawahara (2013). The MSE is the sum of the squared differences between predicted and observed rates. This formula was applied to the data, and the lowest MSE was drawn when the interval parameter ρ was 4. At ρ =4, the model was greatly improved from the baseline model by 83.228% (= (69.5621-11.667)/69.5621*100), as shown in Table 9.

Table 9. Improvements from the baseline at different ρ values

		Baseline	ρ=2	ρ=3	ρ=4	ρ=5	ρ=6
Frequency bins	7.5	8.3521	2.50589	0.0361	0.2788	3.08705	6.3554
	9.6	0.0576	1.78222	4.3597	8.7379	10.595	18.08
	10.9	61.1524	19.9988	9.6472	2.6504	0.04709	0.7413
MSE		69.5621	24.2869	14.043	11.667	13.7292	25.176
Improvements (%)			65.086	79.812	83.228	80.2634	63.807

The two tableaux in (10) below illustrate how the adjustments of faithfulness constraint weights could cause different outputs for frequent and infrequent words in the fourth context (UnstBdry).

(10) The tableaux for the words /editor/ and /comforters/

a. Frequent word /editor/ (log frequency 10.7) in UnstBdry

	w	*nz*	*w*	*nz*	*w*	*nz*	*sf*	*w*	*nz*	
	0.13	2.43	86.28	3.39	80.79	-5.62	-0.53	82.93	-1.45	
/editor/	*ɾ]$_{Mor}$ (2.56)		*Vt^{h}v (89.67)		IDENT-AS (74.64)			*vt^{h}v (81.49)		**H**
edi[t^h]-or								-1		-81.49
☞edi[ɾ]-or	-1				-1					-77.2

(*w*: weight, *nz*: noise, *sf*: scaling factor)

b. Infrequent word /comforters/ (log frequency 6.5) in UnstBdry

	w	*nz*	*w*	*nz*	*w*	*nz*	*sf*	*w*	*nz*	
	0.13	-0.13	86.22	2.08	80.79	-0.49	0.31	82.93	-2.64	
/comforters/	* ɾ]$_{Mor}$ (0.01)		*Vt^{h}v (88.36)		IDENT-AS (80.61)			*vt^{h}v (80.3)		**H**
☞comfor[t^h]-ers								-1		-80.3
comfor[ɾ]-ers	-1				-1					-80.62

In (10a), as the frequency of the word type *editor* (10.7) was higher the reference frequency 8.6, the value of scaling factor (-0.53) (see Table 6) lowers the weight of the faithfulness constraint IDENT-AS. Therefore, the second candidate was selected as the optimal candidate. Contrary to (12a), since the frequency value of the word type *comforters* (6.5) is lower than the reference frequency, the value of the scaling factor (0.31) raises the weight of the faithfulness constraint. Consequently, the first candidate is adopted as the optimal one in (10b).

5. Conclusion

The purpose of this corpus-based study was to examine the gradient aspect of flapping in American English, considering the language-external factor lexical frequency, as well as the language-internal factors stress and morphological complexity. As this project aimed to examine the gradient aspect of flapping, flapping rates were regarded as dependent variables. The conditioning factor stress was used as an independent variable, as were the two factors lexical frequency and morphological complexity. Considering the characteristics of the dependent variables, ZOIB was adopted. The statistical analysis verified that, just as Patterson and Connie

(2001) demonstrated, lexical frequency and morphological complexity both have an effect on flapping. The analysis also confirmed Hong's (2009) confirming that the conditioning factor stress exerts a huge influence on flapping.

Thereafter, a NHG analysis on flapping and the extended version of this analysis with frequency effects modeling were performed, following Coetzee and Kawahara (2013). The flapping rates were predicted according to the learned constraint weights, and the predicted flapping rates and the observed flapping rates were closely correlated to each other by using *Praat*. After the first NHG analysis, which only accommodated the language-internal factors stress and morphological complexity, the language-external factor lexical frequency was encoded within the grammar by adjusting the weight of the faithfulness constraint. The grammar model was improved by 83.228% via this extended version of the NHG analysis.

Appendix A. List of word types in the fourth context (48 types)

FBuckeye: frequency of a word in the Buckeye Speech Corpus
dx: frequency of a word in which a flap occurs
log.freq: log-transformed lexical frequency taken from COCA
[] is used to mark the target phone.

word	FBuckeye	dx	log.freq	word	FBuckeye	dx	log.freq
affirma[t]ive	3	3	8.8	genera[t]ors	1	1	7.7
alterna[t]ive	7	7	10.3	inevi[t]able	2	2	9.2
apprecia[t]ed	1	1	10	informa[t]ive	1	0	7.5
apprecia[t]ive	1	0	7.1	inheri[t]ed	3	2	7.4
authorita[t]ive	1	0	7.7	limi[t]ed	10	6	10
benefi[t]ed	1	1	10.5	marke[t]ing	10	10	9.9
bigo[t]ed	1	1	6	migra[t]ing	1	1	7.3
boyco[tt]ed	1	1	7.9	misinterpre[t]ed	1	1	5.2
chari[t]able	3	3	8.3	modera[t]ing	1	1	9.6
comfor[t]able	14	1	10.2	mutila[t]ed	1	1	4.6
comfor[t]ers	2	0	6.5	nega[t]ive	14	12	10.5
compe[t]ent	1	0	8.5	nega[t]ively	1	0	8.3
concer[t]ed	1	1	9.5	nega[t]ives	2	1	7.3
conserva[t]ive	15	13	10.4	preroga[t]ive	1	0	6.6
conserva[t]ives	2	0	9.3	preserva[t]ive	1	1	5.8

contribu[t]ed	1	1	9.6	rela[t]ive	3	0	10.1
contribu[t]ing	1	1	9.6	rela[t]ives	4	0	9.5
coopera[t]ively	1	1	6.3	secre[t]ive	1	1	7.3
devia[t]ing	1	1	6.2	sena[t]ors	1	0	10.8
edi[t]or	1	1	10.7	targe[t]ed	1	1	10.4
execu[t]ed	3	3	7.9	uncomfor[t]able	4	0	9.2
execu[t]ives	2	2	9.6	unlimi[t]ed	1	1	8.3
forfei[t]ed	1	1	6.6	visi[t]ed	3	3	10.9
forma[t]ive	2	0	7.5	visi[t]ing	2	2	10.9

Appendix B. Sample OT script when the frequency value is 7.5 at ρ=4

```
File type = "ooTextFile"
Object class = "Collection"
size = 2
item[]:
          item[1]:
          class = "OTGrammar 1"
          name = "Gram"
<LinearOT>
4 constraints
constraint [1]: "*D]mor" 0.131 0.131
constraint [2]: "*Vtv" 86.278 86.278
constraint [3]: "Ident(AlveolarStop)" 81.099
81.099
constraint [4]: "*vtv" 82.933 82.933
0 fixed rankings
4 tableaux
input [1]: "PstStrInt:/water/" 2
 candidate [1]: "wa[t]er" 0 1 0 0
 candidate [2]: "wa[D]er" 0 0 1 0

input [2]: "PstStrBdry:/computer/" 2
 candidate [1]: "compu[t]er" 0 1 0 0
 candidate [2]: "compu[D]er" 1 0 1 0

input [3]: "UnstInt:/quality/" 2
 candidate [1]: "quali[t]y" 0 0 0 1
 candidate [2]: "quali[D]y" 0 0 1 0

input [4]: "UnstBdry:/editor/" 2
 candidate [1]: "edi[t]or" 0 0 0 1
 candidate [2]: "edi[D]or" 1 0 1 0
```

```
item [2]:
          class = "PairDistribution"
          name = "current language"
          pairs: size = 8
pairs [1]:
    string1 = "PstStrInt:/water/"
    string2 = "wa[t]er"
    weight = 3.85
pairs [2]:
    string1 = "PstStrInt:/water/"
    string2 = "wa[D]er"
    weight = 96.15
pairs [3]:
    string1 = "PstStrBdry:/computer/"
    string2 = "compu[t]er"
    weight = 5.39
pairs [4]:
    string1 = "PstStrBdry:/computer/"
    string2 = "compu[D]er"
    weight = 94.61
pairs [5]:
    string1 = "UnstInt:/quality/"
    string2 = "quali[t]y"
    weight = 20.90
pairs [6]:
    string1 = "UnstInt:/quality/"
    string2 = "quali[D]y"
    weight = 79.10
pairs [7]:
    string1 = "UnstBdry:/editor/"
    string2 = "edi[t]or"
    weight = 34.31
pairs [8]:
    string1 = "UnstBdry:/editor/"
    string2 = "edi[D]or"
    weight = 65.69
```

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Cheonkam Jeong
Department of English Linguistics
Hankuk University of Foreign Studies
107 Imun-ro, Dongdamun-gu, Seoul
Korea 130-791
e-mail: dorin0123@naver.com

Sung-Hoon Hong
Department of English Linguistics
Hankuk University of Foreign Studies
107 Imun-ro, Dongdamun-gu, Seoul
Korea 130-791
e-mail: hongshoon@hufs.ac.kr

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