Dialect classification using vowel acoustic parameters

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Abstract

This study provides a classification model of two Modern Greek dialects, namely Athenian Greek and Cypriot Greek, using information from formant dynamics of $F1, F2, F3, F4$ and vowel duration. To this purpose, a large corpus of vowels from 45 speakers of Athenian Greek and Cypriot Greek was collected. The first four formant frequencies were measured at multiple time points and modelled using second degree polynomials. The measurements were employed in classification experiments, using three classifiers: Linear Discriminant Analysis, Flexible Discriminant Analysis, and C5.0. The latter outperformed the other classification models, resulting in a higher classification accuracy of the dialect. C5.0 classification shows that duration and the zeroth coefficient of $F2$, $F3$ and $F4$ contribute more to the classification of the dialect than the other measurements; it also shows that formant dynamics are important for the classification of dialect.

Keywords: dialect classification, stress classification, formant dynamics, C5.0, vowels

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1. Introduction

Spoken dialect identification refers to the process of determining the identity of a dialect based on acoustic evidence. There are two main theoretical and methodological approaches to spoken dialect identification. The first originates

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from studies on sociophonetics and aims to explain the variation that exists between dialects, sociolects, speech styles, and registers, and the causes that drive language variation and change (Foulkes & Docherty, 2006; Foulkes et al., 2010; Thomas, 2011, 2013). The second approach is automatic dialect classification, which aims to develop technologies for dialect identification in a wide range of speech processing applications, such as in speech-to-text systems, spoken document retrieval, spoken language translation, and in dialogue systems (see Li et al., 2013, for a review), and may result in high classification accuracy of dialects (see Glembek et al., 2009; Dehak et al., 2010; Behravan et al., 2015). Yet, to model speech variation, automatic dialect classification methods (e.g., Joint Factor Analysis and i-vector architectures), employ hyper-parameters that can be hard to interpret for the purposes of sociophonetic research (see Glembek et al., 2009; Dehak et al., 2010; Behravan et al., 2015).

The purpose of this study is to offer an account of dialect variation in terms of vowel formants and vowel dynamics, using machine learning methods often employed in automatic dialect classification. To this purpose, this study classifies two varieties, Athenian Greek (AG) and Cypriot Greek (CG), whose phonemic inventories contain the same vowels: /i e a o u/ (Kontosopoulos, 1968; Newton, 1972a,b; Samaras, 1974; Botinis, 1981; Tseva, 1989; Jongman et al., 1989; Nicolaidis, 2003; Sfakianaki, 2002; Fourakis et al., 1999; Loukina, 2009, 2011; Themistocleous, 2017). Specifically, AG and CG vowels were produced in controlled settings and measured at multiple time points, which were then evaluated using a second degree (2^{nd}) polynomial fit. This method provides a rich description of vowel formants, as it considers the fluctuation of a formant's frequency with respect to time and does not rely on a single measurement of formants at the middle of the vowel's duration (e.g. Cooper et al., 1952; Lisker, 1957, 1975; Stevens & Klatt, 1974; Rosner & Pickering, 1994; Themistocleous, 2017). The polynomial fit is appealing as each of the coefficients of the polynomial relates to characteristics of a formant contour, such as its position on the frequency axis (zeroth order coefficient) and the shape of the curve (see also Cohen, 1995). Earlier studies by McDougall (2005; 2006) and McDougall

& Nolan (2007) using polynomial equations for regression showed that 2^{nd} and 3^{rd} degree polynomials perform better at 89-96% than raw data and static measurements of vowels (see also Van Der Harst et al., 2014). A key difference of this study with respect to most automatic language identification studies is that it employs a text-dependent approach, whereas most other studies on language identification employ a text-independent approach (see for a discussion of these approaches Atal, 1974; Doddington, 1985; Farrell et al., 1994; Furui, 1997; Gish & Schmidt, 1994; Reynolds & Rose, 1995; Larcher et al., 2014; Mporas et al., 2016).

For the classification, we evaluated three different types of discriminative classifiers: Linear Discriminant Analysis (LDA), Flexible Discriminant Analysis (FDA), and C5.0. These classifiers as opposed to generative models, such as Naive Bayes and Hidden Markov Models (HMMs) do not rely on prior distributions and learned states (Zhang, 2014). The discriminative classifiers identify a class of a specific observation, e.g., the dialect by generalizing from previous measurements. Details for each classifier are provided below.

First, LDA is a classifier, which is very similar to multi-response regression. It permits the evaluation of a binary dependent variable using both continuous and categorical predictors (Harrington & Cassidy, 1999). Specifically, it attempts to find a linear structure in the predictors that can best separate two or more groups. LDA relies on the Bayesian probability, the maximum likelihood assumption, and requires that the data are normally distributed. A number of studies by Najim Dehak and colleagues showed that LDA can potentially provide good classification outcomes when employed in the reduction of i-vector dimensionalities of acoustic properties in state of the art i-vector architectures for speaker (Dehak et al., 2010; Sadjadi et al., 2016), accent (Behravan et al., 2015), and language classification (Dehak et al., 2011; Sizov et al., 2017).

FDA employs non-parametric techniques for the classification of categorical variables (Trevor et al., 1994). So unlike LDA, it does not require that the data are normally distributed. Because not all the predictors of this study are normally distributed, FDA is expected to offer a better classification accuracy than LDA.

C5.0 is a classification algorithm developed by Ross Quinlan (Quinlan, 1993). It assesses class factors, such as the dialect, based on a predefined set of predictors. C5.0 generates a decision tree and offers a ranking of features that can indicate the contribution of each acoustic feature in the classification. Specifically, it evaluates recursively the data and employs the predictors that can provide the best splitting of the data into more refined categories. The splitting criterion is the difference in information entropy (a.k.a., the normalized information gain). The predictor that provides the highest normalized information gain is the one selected for the decision (see also Woehrling et al., 2009, who provide a classification of regional French varieties, using a different decision tree method). Typically, each split is an interpretation of the variation or *impurity* in the data. The algorithm will stop when there are not enough data left to split. Finally, C5.0 provides both tree and rule models (for an application of C4.5, which is an earlier iteration of C5.0, on accent classification, see Vieru et al. (2011) and for the classification of stressed and unstressed fricatives using C5.0, see Themistocleous et al. (2016)).

To evaluate the effects of vowel acoustic properties on dialect classification, we also provide classification results for stress and vowel. A syllable in Modern Greek can be stressed or unstressed; the position of the stress in a Modern Greek word can change the meaning of the word, e.g., miˈlo 'speak' vs. ˈmilo 'apple'. Stressed vowels are overall longer and more peripheral than the unstressed (e.g., Botinis, 1989; Arvaniti, 1991; Themistocleous, 2014, 2015). We also provide comparative classification models for vowels; yet, unlike previous studies that provide acoustic evidence mainly from AG vowels (Kontosopoulos, 1968; Samaras, 1974; Botinis, 1981; Tseva, 1989; Jongman et al., 1989; Nicolaidis, 2003; Sfakianaki, 2002; Fourakis et al., 1999; Loukina, 2009, 2011; Themistocleous, 2017), this study provides cross-dialectal evidence from AG and CG (see, however Themistocleous, 2017). Also, all previous studies on Modern Greek vowels rely on single acoustic measurements of formant frequencies at the middle of the vowel whereas this is the first study to analyze formant dynamics of

Greek vowels.

2. Methodology

This section presents the methods employed for the collection and analysis of the acoustic data. It also presents the selection criteria for the classification model reported in the paper.

2.1. Speakers

A large corpus of AG and CG vowels was recorded in Athens and Nicosia. These urban areas constitute the capital cities of Greece and Cyprus respectively. 45 female speakers between 19 and 29 years participated in the study: 25 CG speakers and 20 AG speakers. All speakers were born and raised in Nicosia and Athens respectively. Based on information from a demographic questionnaire, the participants from each dialect constituted sociolinguistically homogeneous groups: they originated from approximately the same socio-economic background and they were all university students, namely all CG speakers were students at the University of Cyprus and all AG speakers were students at the University of Athens. All participants knew English as a second language; four AG participants knew French as a third language. None reported a speech or hearing disorder.

2.2. Speech Materials

The speech materials consisted of a set of nonsense words, each containing one of the five Greek vowels (/ e i a o u /) in both stressed and unstressed position, word initially and word medially. The nonsense words had the structure V̀*sa* (e.g., /ˈasa, ˈesa, ˈisa, etc./) or V*sà* (e.g., /aˈsa, eˈsa, iˈsa, etc./) sV̀sa (/ˈsasa, ˈsesa, ˈsisa, etc./) and sVsà (/saˈsa, seˈsa, siˈsa, etc./) and were embedded in the following carrier phrases.

The AG carrier phrase was:

"ˈipes < *keyword* > ˈpali" (You told < *keyword* > again)

and the CG carrier phrase was:

Table 1: Speech material

Vowel	stressed	unstressed	stressed	unstressed
/e/	ˈesa	eˈsa	ˈsesa	seˈsa
/i/	ˈisa	iˈsa	ˈsisa	siˈsa
/a/	ˈasa	aˈsa	ˈsasa	saˈsa
/o/	ˈosa	oˈsa	ˈsosa	soˈsa
/u/	ˈusa	uˈsa	ˈsusa	suˈsa

“/ˈipes < *keyword* > ˈpale/” (You told < *keyword* > again).

Each subject produced 80 utterances (i.e., 5 vowels × 2 stress conditions × 2 word placement conditions × 4 repetitions), resulting in a total of 3600 productions. To facilitate vowel segmentation and to control formant transitions at the beginning and the end of a vowel, the voiceless alveolar fricative [s] was selected as the immediate segmental environment–before and after–the designated vowel. Filler words were added in the carrier sentences to provide variation within the experimental material and to minimize speaker’s attention on the experimental words.

2.3. Procedures

The recordings were conducted in a recording studio in Athens, Greece and in a quiet room at the University of Cyprus in Nicosia, for the AG and CG speech material respectively. Two researchers, a female AG speaker and a male CG speaker (the author), provided standard instructions to the speakers before the recording, e.g., to speak at a normal pace, sit appropriately in front of the microphone, and keep a designated distance. The target words were presented in standard Greek orthography (the stress marks are conventionally represented in Greek orthography). All stimuli were randomized. Between the repetitions there was a two-minute break. The speakers read sentences out loud from a computer screen, at a comfortable, self-selected rate. Recordings were made on a Zoom H4n audio recorder where voice was sampled at 44.1 kHz.

For the acoustic analysis, the sounds were analysed by using the open source software Praat 5.3.32 (Boersma & Weenink, 2010). The keywords were located and segmented manually. Specifically, vowel onsets and offsets were located by using simultaneous inspections of the waveform and the spectrogram. Because all measured vowels in the segmental material were interposed between voiceless alveolar fricatives [s], the vowel onset was clearly marked by the beginning of $F2$ and $F1$ and vowel offset by the end of $F2$. Vowel onset was located before the first peak in the periodic waveform and vowel offset was defined as the beginning of the following fricative consonant [s]. The rise of the intensity at the vowel onset and the fall of the intensity at the vowel offset facilitated the segmentation. All segmentation decisions were checked and corrected twice by the first author by using a PRAAT script.

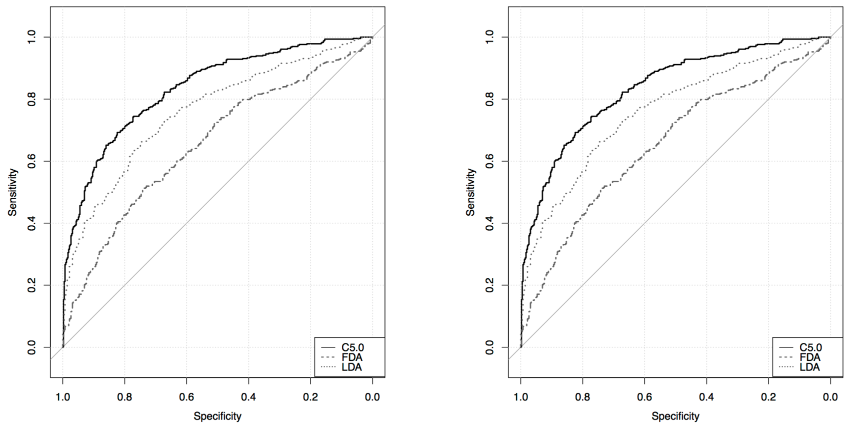
2.4. Measurements

The measurements included the vowel formants ($F1$, $F2$, $F3$, $F4$) and vowel duration. Praat's standard LPC-based method was employed for the extraction of vowel formants.

To model formant dynamics, 9 measurements at 9 equidistant points from the vowel onset to the vowel offset were conducted. Specifically, vowels were measured at the $10-20-30-40-50-60-70-80-90\%$ of vowel duration. In order to avoid any effects of the adjacent consonants, only seven equidistant measurements were included in the final analysis, namely from $20\% - 80\%$ (see for this practice Jacewicz et al., 2011, p. 686). A polynomial fit was employed to model the formant dynamics of $F1$, $F2$, $F3$, and $F4$ and, therefore provide a more detailed and precise characterization of formant frequencies. The N_{th} degree polynomial is given by

$$f_{m,j}(t) = a_{0,m} + a_{1,m}t + a_{2,m}t^2 + \ldots + a_{N-1,m}t^N, \tag{1}$$

where $t = 1, \ldots, 7$ is a discrete index that represents the duration of the vowel and j an index that varies from $1, \ldots, 4$ to denote $F1$, $F2$, $F3$, and $F4$ respectively. The index $m = 1, \ldots, M$ represents the vowel sample approximated



(a) Classification Models for dialect. (b) Classification Models for Stress.

Figure 1: ROC curves for the models generated by the machine learning algorithms C5.0, FDA, LDA for the classification of speech dialect and stress.

with curve fitting. The second degree polynomials employed here result in three polynomial coefficients: the a_0, which corresponds to the starting frequency of the formant, i.e., at the 20% of the actual vowel's duration, whereas the other two coefficients, namely the a_1 and a_2 describe the shape of the vowel formants.

2.5. Model Evaluation

Three classification algorithms, namely C5.0, FDA, and LDA were employed for the classification of dialect, stress, and vowel. Duration and the three formant coefficients of vowel formants were employed as predictors. To evaluate the classification results from the three classifiers, the data were separated into a training set consisting of the 90% of the data (3240 productions) and an evaluation set consisting of the 10% (360 productions) of the data; also, a repeated 10-fold cross validation with 3 repeats was employed.

For model comparison, we employed the receiver operating characteristic (ROC), the sensitivity, the specificity, and the accuracy (see Table 2 and Figure 1). The sensitivity and the specificity are measures for estimating the performance of the binary classifications. The sensitivity shows the proportion of

Table 2: ROC, Sensitivity, Specificity of the models generated by SVM, C5.0, FDA, LDA for the classification of speech dialect.

Category	ROC	Sensitivity	Specificity	method
Dialect	0.83	0.75	0.74	C5.0
	0.78	0.69	0.74	FDA
	0.65	0.68	0.56	LDA
Stress	0.91	0.83	0.83	C5.0
	0.90	0.80	0.83	FDA
	0.89	0.81	0.80	LDA

Table 3: Metrics for the models generated by C5.0, FDA, LDA for the classification of vowel.

Method	logLoss	ROC	Accuracy	Kappa	Sensitivity
C5.0	0.40	0.91	0.83	0.66	0.83
FDA	1.25	0.79	0.54	0.42	0.53
LDA	1.35	0.75	0.49	0.34	0.46

Method	Specificity	Positive Pred.	Negative Pred.	Detection Rate	Balanced Accuracy
C5.0	0.84	0.83	0.83	0.41	0.83
FDA	0.88	0.55	0.88	0.11	0.71
LDA	0.87	0.55	0.87	0.10	0.67

positives that were correctly identified as positives. The specificity indicates the proportion of negatives that were identified correctly as negatives. The ROC curve visualizes these two measures and enables us to compare the curves of the different models and select the best one. The accuracy is the proportion of true results, namely, the true positives and true negatives. In the case of vowel classification, which is not binary, we relied mainly on the accuracy of the model. The ROC curve is created by plotting the sensitivity of the model against the 1 - specificity. The best curve is the one that approaches to the top left corner of the graph whereas a sub-optimal curve is the one that approaches the 45° diagonal of the ROC space (see Figure 1).

Overall, C5.0 performed better than the other classification methods. The worst classifier was LDA, which performed suboptimally. For this reason, the classification results will be reported using C5.0. The statistical analysis and the classification was carried out in R (R Core Team, 2016), using caret (Kuhn, 2016) and the C5.0, package (Kuhn et al., 2015).

3. Results

After curve fitting the vowels, the mean and the standard deviation (SD) of the polynomial coefficients a_0, a_1, a_2 were calculated separately for each vowel, stress, and dialect. The results of the polynomial fitting of vowel formants are reported in Table 4; Figure 2 shows the fitted F1, F2, F3, and F4 of the CG stressed vowels; Figure 3 shows the fitted F1, F2, F3, and F4 of the CG unstressed vowels; Figure 4 shows the fitted F1, F2, F3, and F4 of the AG stressed vowels; and Figure 5 shows the fitted F1, F2, F3, and F4 of the AG unstressed vowels. Table 5 shows the mean duration and the standard deviation for the stressed and unstressed vowels in AG and CG. All vowels differ in their intrinsic duration. Overall, stressed vowels are longer than the unstressed vowels.

The results reported in this section were all generated by C5.0 with a repeated 10-fold cross-validation with 3 repeats. Note that C5.0 automatically drops the variables that do not contribute to the classification so the remaining output always consists from the predictors that contribute to the classification.

Dialect: The classification of the dialect (Accuracy= 0.74, 95% CI [0.71, 0.77], kappa= 0.5) involves all formant frequencies not simply F1, F2, and F3. The coefficients that determine the shape of F2 and F3 are ranked higher than the effects of stress on F1. The contribution of each measurement for the classification of vowels is shown in Table 6.

The duration and the starting frequencies of F2, F3, F4, and F1 have the greatest contribution for the classification of the dialect. The polynomials coefficients that determine the shape of the formant contours also contribute to the classification of dialect.

Stress: The results of the stress classification—cross-validated, 10 fold, re-

Table 4: Mean and SD for of the a_0, a_1, and a_2 polynomial coefficients of F1, F2, F3, and F4.

Vowel	dialect	Stress	F1 a_0	F1 a_0	F1 a_1	F1 a_1	F1 a_2	F1 a_2	F2 a_0	F2 a_0	F2 a_1	F2 a_1	F2 a_2	F2 a_2
			M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
a	CG	Stressed	708.72	196.36	23.09	20.70	-1.45	1.25	1796.25	421.67	6.27	50.30	-0.54	2.96
e	CG	Stressed	567.80	157.86	14.19	18.38	-0.85	0.99	2018.19	427.56	9.35	60.56	-0.78	3.56
i	CG	Stressed	501.40	188.53	12.75	20.33	-0.67	1.18	2262.93	476.78	15.53	52.00	-1.33	2.93
o	CG	Stressed	572.43	166.16	13.69	18.09	-0.83	0.97	1675.04	520.23	0.51	38.17	-0.17	2.48
u	CG	Stressed	507.80	172.26	9.50	25.00	-0.51	1.44	1677.96	558.75	-9.62	62.55	0.63	4.18
a	AG	Stressed	658.45	173.82	25.27	22.33	-1.47	1.22	1779.76	280.62	-2.93	39.73	0.04	2.38
e	AG	Stressed	577.05	119.94	21.29	17.45	-1.25	0.89	1934.62	266.63	3.09	37.96	-0.37	2.23
i	AG	Stressed	478.81	144.17	14.44	20.81	-0.75	1.07	2123.36	351.08	9.85	39.54	-0.85	2.18
o	AG	Stressed	560.13	104.70	21.40	21.49	-1.20	1.13	1576.28	330.91	-11.44	38.11	0.46	2.30
u	AG	Stressed	478.65	117.06	15.08	23.27	-0.74	1.18	1568.11	377.44	-14.20	43.80	0.74	2.75
a	CG	Unstressed	663.27	184.51	14.19	21.69	-1.03	1.26	1791.61	402.67	-3.50	41.37	-0.08	2.71
e	CG	Unstressed	529.05	157.27	8.38	25.98	-0.59	1.47	2026.28	392.70	1.26	50.83	-0.41	3.28
i	CG	Unstressed	475.62	167.96	8.91	26.35	-0.53	1.59	2223.61	464.10	6.33	50.91	-0.82	2.97
o	CG	Unstressed	535.95	158.42	7.07	27.17	-0.50	1.60	1725.24	439.36	-14.28	55.03	0.60	3.89
u	CG	Unstressed	483.44	173.78	2.05	32.87	-0.05	2.13	1803.20	491.43	-22.73	61.84	1.40	4.29
a	AG	Unstressed	584.78	166.34	15.53	23.39	-1.06	1.35	1797.82	272.49	-7.92	22.99	0.25	1.60
e	AG	Unstressed	513.77	155.02	11.27	24.51	-0.77	1.34	1943.32	257.05	-0.95	24.80	-0.27	1.59
i	AG	Unstressed	461.38	184.00	7.98	30.73	-0.41	1.94	2109.45	314.76	-0.33	28.09	-0.40	1.78
o	AG	Unstressed	528.68	143.61	0.45	39.38	-0.02	2.44	1643.82	321.36	-26.41	45.34	1.43	3.13
u	AG	Unstressed	497.87	185.21	-10.30	54.16	0.85	3.51	1708.39	348.29	-31.10	48.11	1.80	3.47
			F3 a_0	F3 a_0	F3 a_1	F3 a_1	F3 a_2	F3 a_2	F4 a_0	F4 a_0	F4 a_1	F4 a_1	F4 a_2	F4 a_2
			M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
a	CG	Stressed	2833.48	369.66	-15.01	68.13	0.77	3.96	4010.19	801.41	-42.97	98.32	2.36	5.74
e	CG	Stressed	2882.91	344.33	-8.74	56.69	0.54	3.37	3919.62	856.75	-40.44	97.03	2.42	5.67
i	CG	Stressed	3000.88	307.24	-1.39	45.86	-0.11	2.83	4015.08	928.47	-18.64	64.90	0.85	3.65
o	CG	Stressed	2965.85	311.88	-5.72	46.86	0.22	2.86	4030.25	590.04	-22.72	51.29	1.20	3.06
u	CG	Stressed	3011.21	293.61	-9.97	54.80	0.48	3.31	3886.92	857.30	-18.48	60.04	0.93	3.58
a	AG	Stressed	2870.93	222.36	-26.99	50.68	1.50	2.90	4086.23	666.12	-41.91	81.15	2.34	4.83
e	AG	Stressed	2897.85	224.56	-19.24	48.33	1.05	2.66	4087.10	795.51	-44.94	86.77	2.42	4.93
i	AG	Stressed	2930.61	189.79	-11.09	36.12	0.53	1.96	4166.19	599.72	-31.64	72.62	1.58	4.32
o	AG	Stressed	2882.88	209.80	-21.57	38.26	1.12	2.18	3766.96	626.73	-15.84	60.19	0.82	3.41
u	AG	Stressed	2868.23	193.82	-15.08	40.21	0.67	2.20	3713.15	700.25	-20.33	62.87	1.07	3.67
a	CG	Unstressed	2873.43	370.59	-22.79	63.68	1.37	3.91	3944.07	1089.24	-23.92	75.65	1.41	4.70
e	CG	Unstressed	2951.65	310.55	-16.92	52.07	0.90	3.22	4051.97	945.40	-18.31	64.77	1.00	3.98
i	CG	Unstressed	3012.94	296.61	-10.91	45.54	0.39	2.79	4032.84	1044.23	-9.96	46.12	0.33	2.72
o	CG	Unstressed	3020.32	318.88	-18.18	55.19	1.02	3.37	3946.60	989.19	-16.98	42.98	0.92	2.76
u	CG	Unstressed	3100.34	320.73	-23.24	48.13	1.35	3.08	3825.24	1094.19	-18.50	48.67	1.05	3.15
a	AG	Unstressed	2926.55	204.49	-14.78	32.40	0.72	1.96	4192.51	613.37	-12.56	51.33	0.44	3.17
e	AG	Unstressed	2954.14	204.89	-11.38	32.61	0.47	1.80	4225.25	605.10	-8.06	67.08	0.17	3.83
i	AG	Unstressed	2972.61	207.23	-11.19	29.80	0.44	1.85	4206.72	655.20	-8.02	44.32	0.06	2.62
o	AG	Unstressed	2927.39	233.22	-23.65	37.24	1.33	2.29	3800.89	579.00	-20.60	53.87	1.18	3.31
u	AG	Unstressed	2915.60	235.14	-28.97	40.67	1.65	2.66	3727.32	785.16	-26.68	62.37	1.69	3.90

Table 5: Mean duration and standard deviation (in ms) for the AG and CG vowels in stressed and unstressed positions.

	AG				CG			
	Stressed		Unstressed		Stressed		Unstressed	
Vowels	M	SD	M	SD	M	SD	M	SD
/e/	133	28	78	21	137	24	94	19
/i/	115	30	58	20	118	28	83	21
/a/	142	27	94	19	149	26	107	20
/o/	140	28	84	20	139	25	96	22
/u	121	30	68	19	123	27	82	21

peated 3 times—yielded a 83% accuracy, (kappa= 0.7). The contribution of each measurement for the classification of vowels is shown in Table 7.

Specifically, duration and F1 a_1/ a_2, F2 a_2, and F4 contribute more to the classification of stressed vs. unstressed vowels. What is more important however, is that all acoustic properties contribute in different degrees, especially the polynomial coefficients that determine the shape of vowel formants. Notably, the latter suggests that stress has an effect on the formant contour as a whole.

Vowels: The classification of vowel shows that all predictors contribute significantly for the classification of vowel categories (classification accuracy= 0.57, 95% CI[0.5355, 0.6021], Kappa = 0.5). The best classification results were obtained for vowel /i/, /u/, and /e/ and the worst for /a/ and /o/. The contribution of each measurement for the classification of vowels is shown in Table 9.

The polynomial coefficients of $F1$ and the polynomial coefficients of $F2$ and $F3$ are the most important properties for the classification of vowels. In addition to the first three formants, $F4$ and duration also contribute to the classification of vowels.

Table 6: Rankings of the variable contribution for the classification of dialect.

Rank	Variable
100 %	duration
100 %	F2 a_0
100 %	F3 a_0
100 %	F4 a_0
99.04 %	F1 a_0
99.03 %	F2 a_2
99.03 %	F3 a_2
99.02 %	F2 a_1
92.51 %	F3 a_1
92.30 %	F1 a_1
91.21 %	F4 a_1
86.36 %	F1 a_2
80.15 %	F4 a_2

Table 7: Rankings of the variable contribution for the classification of stress.

Rank	Variable
100%	duration
100%	F1 a_1
100%	F1 a_2
99.99%	F2 a_2
99.99%	F4 a_0
99.99%	F4 a_1
99.97%	F2 a_1
99.97%	F3 a_2
99.77%	F3 a_0
99.17%	F2 a_0
98.71%	F1 a_0
91.03%	F3 a_1
84.85%	F4 a_2

Table 8: Classification matrix with the percentage of correctly classified vowels.

classified as	a	e	i	o	u
a	89.30	2.17	6.36	1.41	0.76
e	3.37	91.34	3.64	1.10	0.55
i	2.11	1.24	95.78	0.31	0.56
o	2.43	1.25	4.09	88.83	3.40
u	2.85	0.63	3.20	1.88	91.45

Table 9: Rankings of the variable contribution for the classification of vowel.

Rank	Variable
100%	F1 a_0
100%	F1 a_1
100%	F1 a_2
100%	F2 a_0
100%	F2 a_1
100%	F2 a_2
100%	F3 a_0
100%	F3 a_1
100%	F3 a_2
100%	F4 a_0
99.79%	duration
99.77%	F4 a_1
98.92%	F4 a_2

4. Discussion

In this study, we ran a number of classification experiments using vowel data from two Greek dialects: AG and CG. Specifically, this study tested and evaluated three different types of discriminative classifier before focusing in just one, C5.0, which was found to outperform the other two classifiers, namely the LDA and the FDA in the classification of dialect. The study provides for the first time acoustic evidence of AG and CG formant dynamics, as all previous studies on Greek vowels rely on a single measurement at the middle of the vowel formant (Kontosopoulos, 1968; Samaras, 1974; Botinis, 1981; Tseva, 1989; Jongman et al., 1989; Nicolaidis, 2003; Sfakianaki, 2002; Fourakis et al., 1999; Loukina, 2009, 2011; Themistocleous, 2017). It also provides for the first time evidence of the $F3$ and $F4$ of Cypriot Greek vowels. More importantly, the study shows that formant measurements of $F1$–$F4$, dynamic measurements, and duration result in high classification accuracy of these two varieties using C5.0 decision trees.

An advantage of the method employed in this study is that it resulted in a classification of Greek dialects, using features from vowels that can be readable by humans and can be interpreted from a sociophonetic point of view to explain sociophonetic variation. In other words, the classification explains how dialect affects formant dynamics, and vowel duration, using the actual values of formants and duration. Notably, C5.0 classification showed that the most significant acoustic properties for the classification of the two Greek dialects are duration and the polynomial coefficients of $F2$, $F3$, $F4$, and $F1$—in this order. Also, it showed that the effects of the dialect pertain higher order formants, such as $F3$ and $F4$. In fact, $F4$ contributes more to the classification of dialect than $F1$, which—along with $F2$—plays an important role for the classification of vowel and stress. Overall, our findings indicate that the effects of dialect are not located on specific acoustic properties of vowels but affect all measured acoustic properties in different degrees, as became evident by the ranking of the acoustic measurements in the classification model.

With respect to stress, the classification showed that stressed vowels are longer than unstressed vowels. This finding corroborates earlier studies on CG (Themistocleous, 2017) and AG vowels (e.g., Botinis, 1989; Arvaniti, 1991; Fourakis et al., 1999; Loukina, 2009, 2011; Themistocleous, 2017). More specifically, the classification demonstrated that duration contributes greatly to the distinction between stressed and unstressed vowels (e.g., see Jongman et al., 1989; Nicolaidis, 2003; Arvaniti, 1991, 2000; Sfakianaki, 2002; Fourakis et al., 1999; Themistocleous, 2017). Moreover, the formant dynamics of AG and CG vowels also contribute to the classification of stress, that became evident by the contribution of a_1 and a_2 polynomial coefficients, which determine the shapes of the contours of $F1$ and $F2$ in the classification of stress. In fact, their ranking in the classification was higher than that of the starting frequency (i.e., the a_0), which suggests that there is a difference in the shape of the formant contours of stressed and unstressed vowels.

The most significant factors for the classification of vowels are the polynomial coefficients of $F1$ followed by the polynomial coefficients of $F2$. So, the findings corroborate earlier studies, which suggest that $F1$ and $F2$ are the most significant formant frequencies for the classification of vowels (e.g. Cooper et al., 1952; Lisker, 1957, 1975; Stevens & Klatt, 1974; Rosner & Pickering, 1994). Also, AG and CG differ in the $F3$ formant frequency, which follows $F1$ and $F2$ in significance based on the C5.0 ranking. This finding is consistent with previous findings by Themistocleous (2017), who shows that AG high vowels /i u/ and the back /o/ had a significantly lower $F3$ than the corresponding CG vowels; this suggests that AG vowels are characterized by more lip-rounding than the corresponding CG vowels (Themistocleous, 2017). Also, a_1 and a_2 polynomial coefficients of vowel formants were employed for the classification of vowels. These coefficients determine the shape of the formant contour, which suggests that the overall shape of formant contours differs form vowel to vowel. Note that the duration in the classification of vowels is ranked lower than in the case of stress and dialect, which suggests that formants are more important than duration for the classification of Greek vowels.

Overall, the same acoustic measurements can distinguish the dialect, the stress, and the vowel. The ranking of acoustic measurements determines the classification results in the three classification cases. For instance, for the classification of dialect and stress, C5.0 classifier identifies the duration as a more important factor than vowel formants. Also, it identifies $F4$ as more important for the classification of dialect than for the classification of vowels.

To conclude, this work established the effects of the acoustic properties of AG and CG vowels in highly controlled settings for the classification of dialect, vowel, and stress. Overall, text-dependent studies such as this one can result in high accuracy. In a future study, it is worth comparing these findings with a text-independent study of vowels produced in other types of speech data and in more realistic, less-controlled scenarios.

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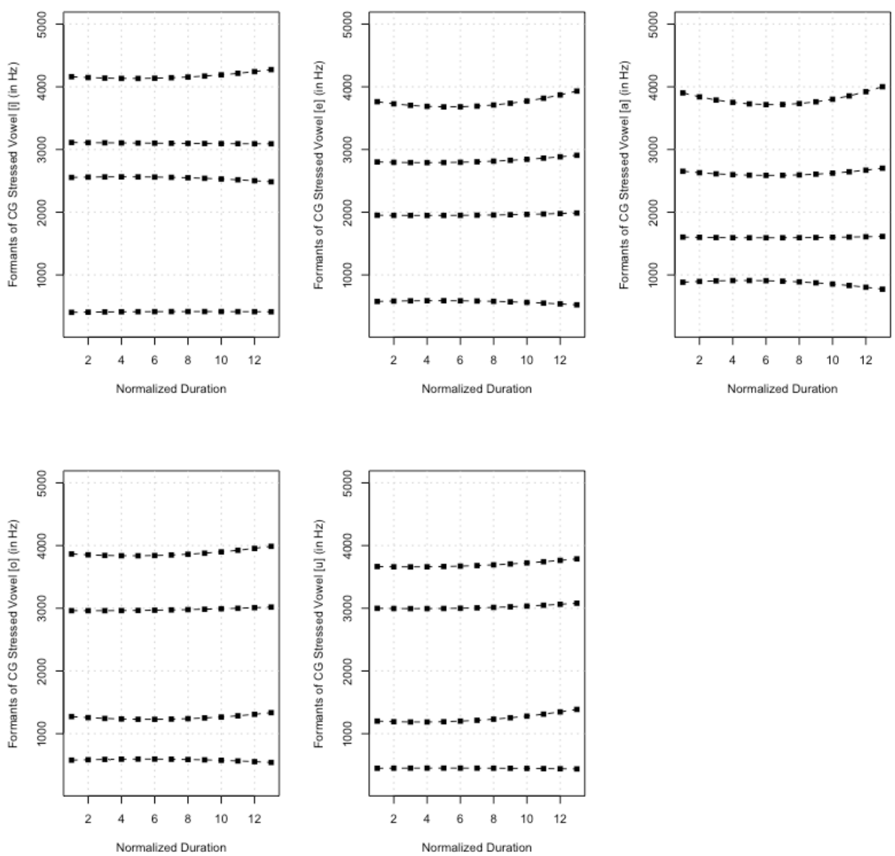

Figure 2: CG stressed vowel formants modelled using polynomial fitting. The horizontal lines from bottom to top represented the F1, F2, F3, and F4 formant frequencies of Greek vowels [i e a o u].

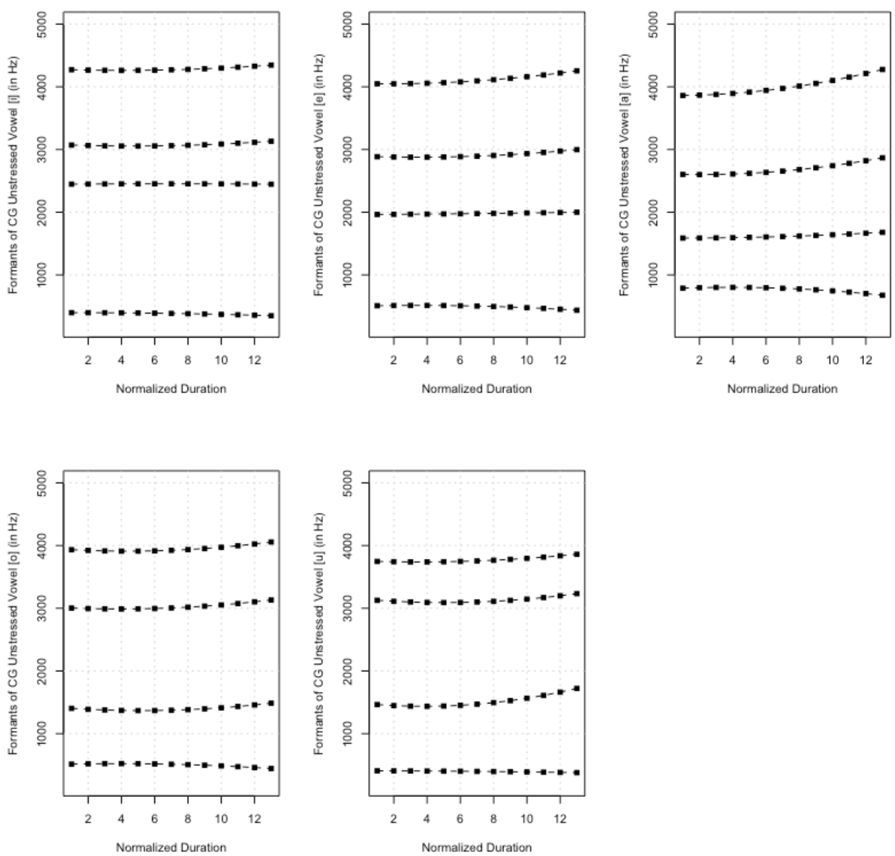

Figure 3: CG unstressed vowel formants modelled using polynomial fitting. The horizontal lines from bottom to top represented the F1, F2, F3, and F4 formant frequencies of Greek vowels [i e a o u].

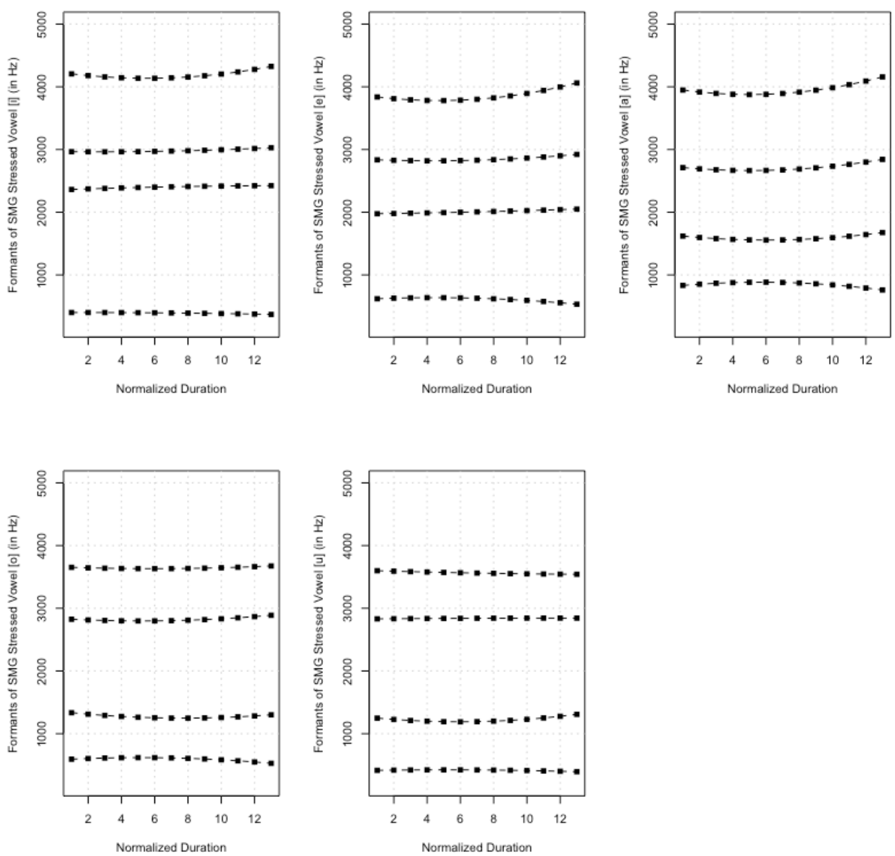

Figure 4: CG stressed vowel formants modelled using polynomial fitting. The horizontal lines from bottom to top represented the F1, F2, F3, and F4 formant frequencies of Greek vowels [i e a o u].

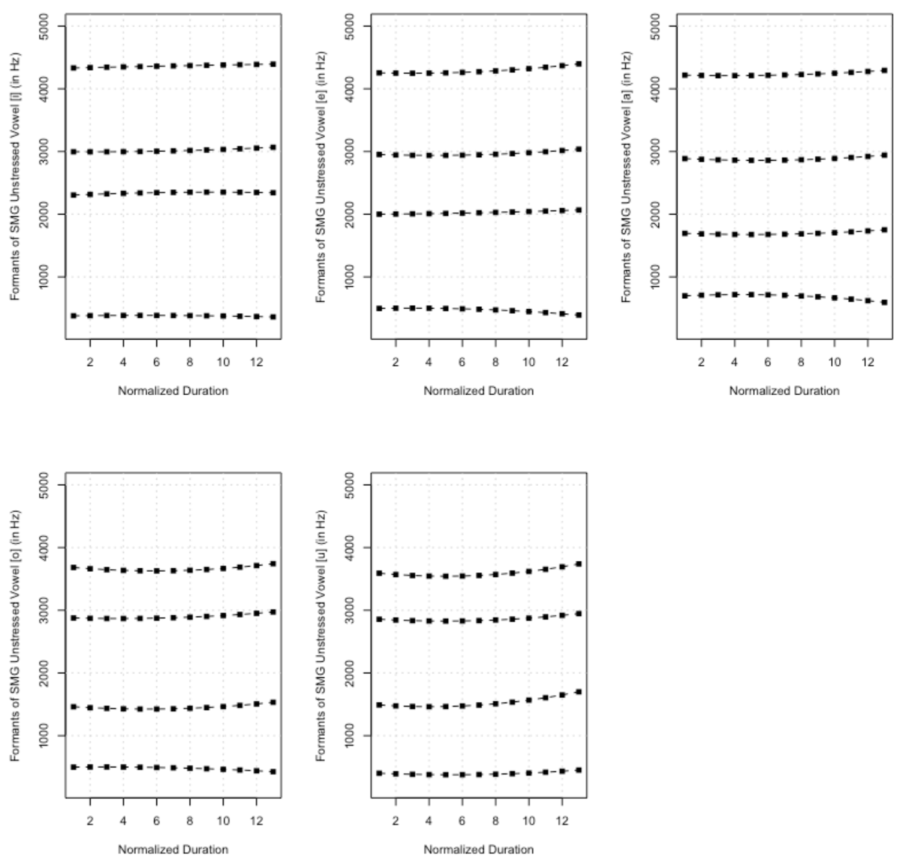

Figure 5: CG unstressed vowel formants modelled using polynomial fitting. The horizontal lines from bottom to top represented the F1, F2, F3, and F4 formant frequencies of Greek vowels [i e a o u].