CHARACTERIZATION OF PATHOLOGICAL VOICE SIGNALS BASED ON CLASSICAL ACOUSTIC ANALYSIS

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Abstract: This work describes a method used to classify voice signals as normal or pathological. Voices were chosen from the KAY ELEMETRICS CORP Voice Disorders Database. The process of characterization of the voices as normal or pathological was done using classical acoustic analysis characteristics. Individual features gave false positive and false negative rates ranging from 15% up. By using three features simultaneously false positive and false negative rates of 13% and 15%, respectively, were obtained.

Key Words: voice characterization, pathological voice, acoustic analysis, noninvasive.

1. INTRODUCTION

The human voice is an efficient means of communication. Unfortunately various pathologies hinder verbal communications. Acoustic analysis has been useful in assisting voice professionals in detecting voice pathologies.

One very positive point in acoustic analysis is the fact that it is a noninvasive measurement. This reduces the patient´s resistance to the treatment. Invasive measurement can be quite uncomfortable, and therefore creates more resistance of the patient toward this.

Various studies have been published in the last several years suggesting methods for classifying voices into normal or pathological. In general, these methods use the classical approach, using pitch and amplitude variations, plus the presence of sub-harmonic components and signal distortion [1-2].

Several other techniques have been proposed, like glottal noise estimation [3-5]; time-frequency parameter extraction [6] wavelet transformations [7-8] and others based on the linear prediction model, and cepstral parameters [9-20].

Unfortunately, researchers have not come to a consensus as to which acoustic features are best suited to discriminate between normal and pathological voices, leaving the field wide open to additional research. This work investigates the combination of features of classical acoustical analysis of voice signals in the attempt of increasing the correct classification of voices.

2. OBJECTIVES

This work aims to characterize pathological voice signals, by way of classical acoustic analysis, combining several features. Algorithms have been developed to process voice signals, from the KAY ELEMETRICS CORP Voice Disorders Database, using three or five features simultaneously in the classification as normal or pathological.

3. ACOUSTIC ANALYSIS

The following acoustic features were analyzed: APQ, ATRI, Fatr, Jita, Jitt, NHR, PPQ, RAP, sAPQ, ShdB, Shim, sPPQ, vAm, VTI (fourteen in all). For each feature, the Receiver Operating Characteristic curves were calculated and plotted, the EER (Equal Error Rate) threshold (ie, the point for which the false positive rate equals the false negative rate) was calculated, along with the AUC (Area Under the Curve). The optimum False Positive and False Negative rates were also calculated based on the EER threshold.

From this group, the features with the highest AUC and the lowest EER were chosen. Those were: Jita, NHR, RAP, sAPQ, and ShdB. They were, then, calculated together using a majority vote algorithm.

It was observed that the features that are of short-term duration gave higher AUC than those of long-term duration. The meaning and method of calculation of each feature is described below.

APQ - Amplitude Perturbation Quotient /%/ - is the relative evaluation of the period-to-period variability of the peak-to-peak amplitude within the analyzed voice sample at smoothing of 11 periods.

$$APQ = \frac{\frac{1}{N-4}\sum_{i=1}^{N-4}\left|\frac{1}{5}\sum_{r=0}^{4}A^{i+r}-A^{i+2}\right|}{\frac{1}{N}\sum_{i=1}^{N}A^{(I)}} \qquad \text{Eq. 1}$$

where: A(i), i=1,2...N is the extracted peak-to-peak amplitude data, and N is the number of extracted impulses.

Jita - Absolute Jitter /usec/ - An evaluation of the period-to-period variability of the pitch period within the analyzed voice sample. Jita is computed from the extracted period-to-period pitch data as:

$$Jita = \frac{1}{N-1}\sum_{i=1}^{N-1}\left|To^{(i)} - To^{(i+1)}\right| \qquad \text{Eq. 2}$$

where: To(i) , i=1,2...N - extracted pitch period data,
N = PER - number of extracted pitch periods.

NHR - Noise-to-Harmonic Ratio - Average ratio of the inharmonic spectral energy in the frequency range 1500-4500 Hz to the harmonic spectral energy in the frequency range 70-4500 Hz. This is a general evaluation of noise present in the analyzed signal.

RAP - Relative Average Perturbation /%/ - is the relative evaluation of the period-to-period variability of the pitch within the analyzed voice sample with smoothing factor of 3 periods.

$$RAP = \frac{\frac{1}{N-2}\sum_{i=2}^{N-1}\left|\frac{To^{(i-1)}+To^{(i)}+To^{(i+1)}}{3}-To^{(i)}\right|}{\frac{1}{N}\sum_{i=1}^{N} To^{(i)}} \qquad \text{Eq. 3}$$

where: To(i), i=1,2...N is the extracted pitch period data, N = PER is the number of extracted pitch periods.

sAPQ - Smoothed Amplitude Perturbation Quotient /%/ - Relative evaluation of the short- or long-term variability of the peak-to-peak amplitude within the analyzed voice sample at smoothing factor of 55 periods.

$$sAPQ = \frac{\frac{1}{N-sf+1}\sum_{i=1}^{N-sf+1}\left|\frac{1}{sf}\sum_{r=0}^{sf-1} A^{(i+r)}-A^{(i+m)}\right|}{\frac{1}{N}\sum_{i=1}^{N} A^{(i)}} \qquad \text{Eq. 4}$$

where: A(i), i=1,2...N is the extracted peak-to-peak amplitude data, N is the number of extracted impulses and sf - smoothing factor.

ShdB - Shimmer in dB /dB/ - Evaluation in dB of the period-to-period (very short-term) variability of the peak-to-peak amplitude within the analyzed voice sample. ShdB is computed from the extracted peak-to-peak amplitude data as:

$$ShdB = \frac{1}{N-1}\sum_{i=1}^{N-1}\left|20\log\left(A^{(i+1)}/_{A^{(i)}}\right)\right| \qquad \text{Eq. 5}$$

where: A(i), i=1,2...N is the extracted peak-to-peak amplitude data, and N is the number of extracted impulses.

4. ANALYZED VOICES

The voices that were used were selected from the KAY ELEMETRICS CORP Voice Disorders Database [21]. This database consists of over 700 subjects (53 subjects with normal voices and 657 subjects with pathological voices). Each subject recorded a sustained vowel for up to 3 seconds and the first few seconds of the "Rainbow Passage". The voice samples were recorded in a sound-proof booth using a condenser microphone placed at 15 cm from the mouth. All recordings were sampled at 44.1 kHz on a DAT-recorder and later resampled to 25 kHz or 50 kHz and saved in files on the computer.

In this work, samples were chosen from the sustained vowel collection. The selected files are listed in the Appendix.

5. METHOD

For each of the fourteen features, the EER (Equal Error Rate) and the AUC (Area Under the Curve) was calculated. The six features that resulted in the lowest EER and highest AUC were chosen for the second part of the study. The ROC curves are presented in Figures 1 through 6.

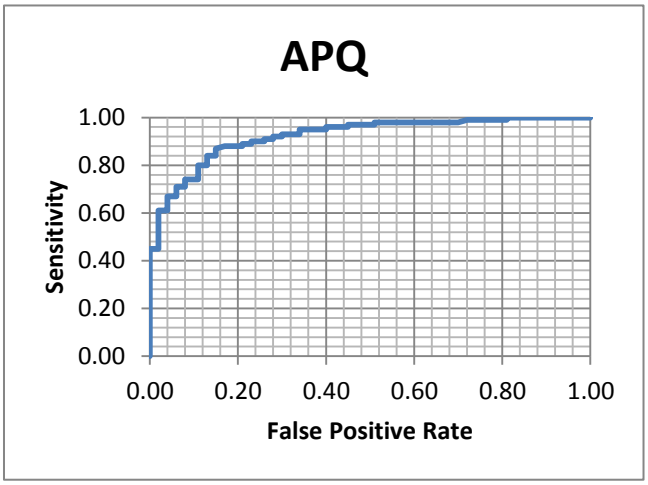

Figure 1 – APQ ROC curve plot.

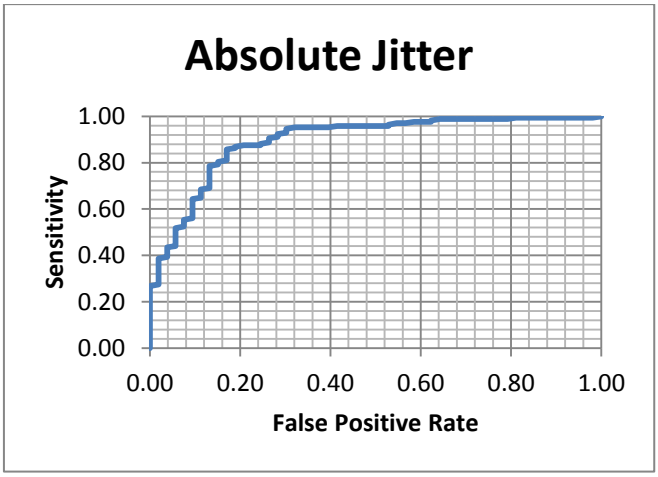

Figure 2 – Absolute Jitter (Jita) ROC curve plot.

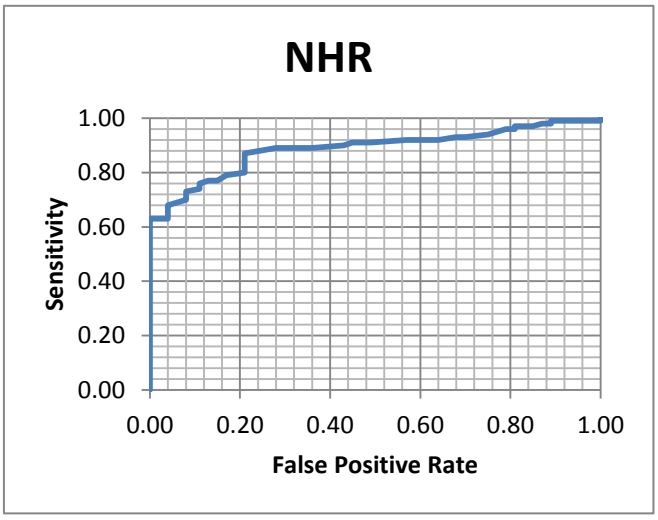

Figure 3 – Noise to Harmonics Excitation Ratio ROC curve plot.

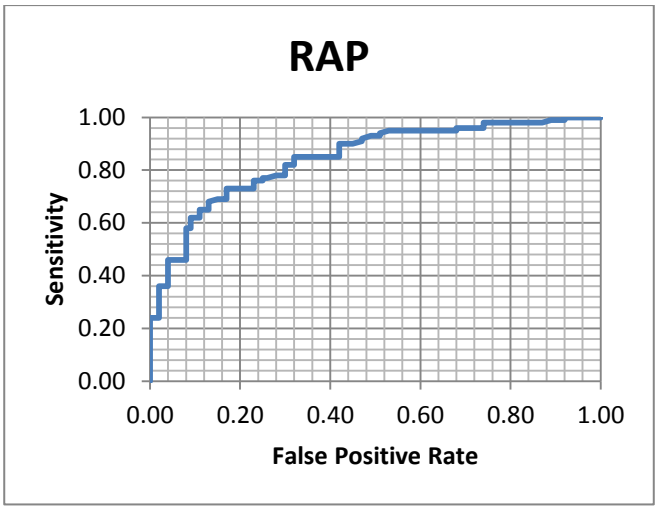

Figure 4 – RAP ROC curve plot.

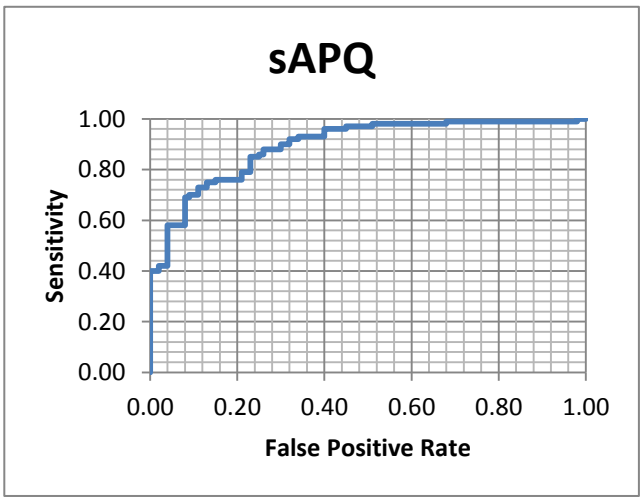

Figure 5 – sAPQ ROC curve plot.

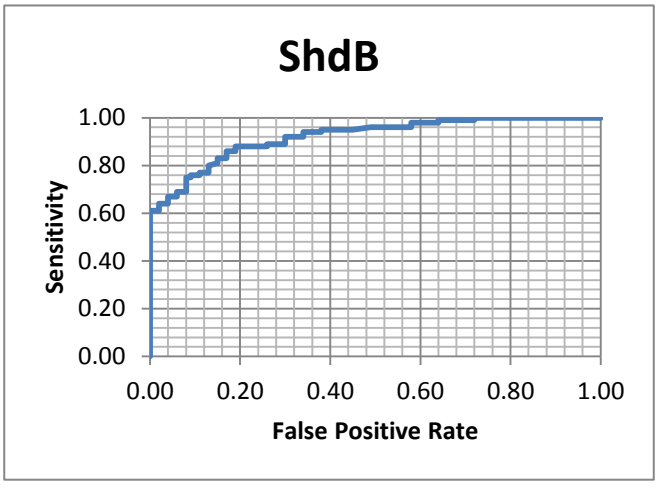

Figure 6 – ShdB ROC curve plot.

The resulting values of EER and AUC for the selected features are presented in Table 1, along with the number of voice signals used in each calculation.

Table 1 – EER in % and AUC

Feature	EER%	AUC	# Voices
APQ - Amplitude Perturbation Quotient	15.29	**0.92**	221
Jita - Absolute Jitter	17.12	**0.90**	221
NHR - Noise to Harmonic Ratio	20.79	0.89	221
RAP - Relative Average Perturbation	23.52	0.85	221
sAPQ - Smoothed Amplitude Perturbation Quotient	20.98	0.89	218
ShdB - Shimmer in dB	17.12	**0.92**	221

Next, the EER% was used to calculate the EERT (Equal Error Rate Threshold), the FP (False Positive) and FN (False Negative) values, as presented in Table 2.

Table 2 – Individual feature values.

Feature	EERT	FP	FN
APQ - Amplitude Perturbation Quotient	2.31	15.09	15.48
Jita - Absolute Jitter	42.73	16.98	17.26
NHR - Noise to Harmonic Ratio	0.13	20.75	20.83
RAP - Relative Average Perturbation	0.45	22.64	24.40
sAPQ - Smoothed Amplitude Perturbation Quotient	3.58	20.75	21.21
ShdB - Shimmer in dB	0.28	16.98	17.26

6. EXPERIMENTAL RESULTS

The three features with the highest AUC and lowest EER were selected and were evaluated collectively, using a majority vote algorithm. Results are presented in Table 3. By evaluating the features together, the FP (False Positive) rate was reduced by 2% (in relation to the best individual score) and the FN (False Negative) rate was maintained.

Table 3 – Three features evaluated together

Feature	EERT	FP	FN
APQ - Amplitude Perturbation Quotient	2.31	15.09	15.48
Jita - Absolute Jitter	42.73	16.98	17.26
ShdB - Shimmer in dB	0.28	16.98	17.26
Calculated together	[1]	13.21	15.48

[1] The 3 individual EERTs were used for each feature, and the majority vote algorithm calculated the combined FP and FN rates.

The last part was to make groups of five features and evaluate them collectively, using the majority vote algorithm. Results are presented in Table 4 and Table 5. For Table 4, HNR and sAPQ were added to the features in Table 3. For Table 5, sAPQ was substituted for RAP.

It can readily be seen that there was an increase in the False Negative rate in both attempts. The False Positive rate was only as good as the results with three features (Table 3).

Table 4 – Collective evaluation of APQ, Jita, NHR, sAPQ and ShdB

Feature	EERT	FP	FN
APQ - Amplitude Perturbation Quotient	2.31	15.09	15.48
Jita - Absolute Jitter	42.73	16.98	17.26
NHR - Noise to Harmonic Ratio	0.13	20.75	20.83
sAPQ - Smoothed Amplitude Perturbation Quotient	3.58	20.75	21.21
ShdB - Shimmer in dB	0.28	16.98	17.26
Calculated together	[2]	13.21	16.97

Table 5 – Collective evaluation of APQ, Jita, NHR, RAP, and ShdB

Feature	EERT	FP	FN
APQ - Amplitude Perturbation Quotient	2.31	15.09	15.48
Jita - Absolute Jitter	42.73	16.98	17.26
NHR - Noise to Harmonic Ratio	0.13	20.75	20.83
RAP - Relative Average Perturbation	0.45	22.64	24.40
ShdB - Shimmer in dB	0.28	16.98	17.26
Calculated together	[2]	13.21	18.45

7. CONCLUSIONS

Acoustic analysis can help gather information about a speaker's voice in a noninvasive manner. This information can be used in the classification of voices as being normal or pathological. The features that are calculated based on the short-term interval produce a more accurate classification.

Combining the three features with the lowest EER in a majority vote classifier results in a lower EER than any of the features measured individually. Combining five features simultaneously doesn't give us a higher accuracy, presumably because of the much higher EER of the added features.

REFERENCES

[1] C.H.Espinosa et al. "*Diagnosis of Vocal Disorders by the Speech Signal"* IEEE-INNS-ENNS Internation Joint Conference on Neural Networks (IJCNN'00) Como, Italy, IEEE 2000.

[2] C. Manfredi "*Adaptive Noise Energy Estimation in Pathological Speech Signals"* IEEE Transactions on Biomedical Engineering, November 2000.

[3] K. Shama, A. Krishna, N. U. Cholayya *"Study of Harmonics-to-Noise Ratio and Critical-Band Energy Spectrum of Speech as Acoustic Indicators of Laryngeal and Voice Pathology"* EURASIP Journal on Advances in Signal Processing, 2007.

[4] P.J.Murphy, O.O.Akande "*Noise Estimation in Voice Signals using Short-Term Cepstral Analysis*" Journal of the Acoustical Society of America, 2007.

[5] C. Jo, T. Li, J. Wang "*Estimation of Harmonic and noise Components from Pathological Voice using Interactive Method"* Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th annual Conference, Shanghai, China, September 2005.

[6] K. Umapathy, S. Krishnan, V. Parsa, D. G. Jamieson *"Discrimination of Pathological Voices Using a Time-Frequency Approach"* IEEE Transactions on Biomedical Engineering, March, 2005.

[7] E. S. Fonseca et al. *"DiscreteWavelet Transform and Support Vector Machine Applied to Pathological Voice Signals Identification",* Proceedings of the 7th IEEE International Symposium on Multimedia (ISM'05), 2005.

[8] P. Kukharchik, D. Martynov, I. Kheidorov, O.Kotov, *"Vocal Fold Pathology Detection using Modified Wavelet-like Features and Support Vector Machines"* EURASIP EUSIPCO, 2007.

[9] B. G. Aguiar Neto, S. C. Costa, J. M. Fechine, M. Muppa *"Feature estimation for Vocal Fold Edema Detection Using Short-Term Cepstral Analysis."*, Proceedings of the 7th IEEE International Conference on Bioinformatics and Engineering, October, 2007.

[10] B. G. Aguiar Neto, S. C. Costa, J. M. Fechine, M. Muppa, *"Acoustic Features of Disordered Voices Under Vocal Fold Pathology"*, 19th international Congress on Acoustics, (ICA'07), September, 2007.

[11] S. M. Zitta, *"Análise Perceptivo-Auditiva e Acústica em Mulheres com Nódulos Vocais"*, Master's thesis Centro Federal de Educação Tecnológica – CEFET-PR Paraná, Brasil, 2005.

[12] J. I. Godino-Llorente, P. Gomez-Vilda, M. Blanco-Velasco, *"Dimentionality Reduction of a Pathological Voice Quality Assessment System Based on Gaussian Mixture Models and Short-Term Cepstral Parameters"* IEEE Transactions on Biomedical Engineering, October, 2006.

[13] A. A. Dibazar, T. W. Berger, S. S. Narayanan, *"Pathological Voice Assessment"*, Proceedings of the 28th IEEE Annual Engineering in Medicine and Biology Society Conference (EMBS'06), 2006.

[14] M. Bahoura, C. Pelletier, *"Respiratory Sounds Classification using Cepstral Analysis and Gaussian Mixture Models"*, Proceedings of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, September, 2004.

[15] T. L. Eadie, P. C. Doyle, *"Classification of Dysphonic Voice: Acoustic and Auditory-Perceptual Measures"* Journal of Voice, Vol 19, Number 1, 2005.

[2] The 5 individual EERTs were used for each feature, and the majority vote algorithm calculated the combined FP and FN rates.

[16] J. I. Godino-Llorente, P. Gómez-Vilda, *"Automatic Detection of Voice Impairments by means of Short-Term Cepstral Parameters and Neural Network Based Detectors"*, IEEE Transactions on Biomedical Engineering, Vol 51, number 2, February, 2004.

[17] M. Marinaki, C. Kotropoulos, I. Pitas, N. Maglaveras, *"Automatic Detection of Vocal Fold Paralysis and Edema"* Proceddings of the International Conference on SpokenLanguage Processing (ICSLP), October, 2004.

[18] J. I. Godino-Llorente, S. Aguilera-Navarro, P. Gómez-Vilda, *"Automatic Detection of Voice Impairments due to Vocal Misuse by means of Gaussian Mixture Models"*, Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October, 2001.

[19] S. L. N. C. Costa, *"Análise Acústica, Baseada no Modelo Linear de Produção de Fala, para Discriminação de Vozes Patológicas"* Doctoral thesis, Universidade Federal de Campina Grande – UFCG, Campina Grande, Paraíba, Brasil, 2008.

[20] C. Kotropoulos, G. R. Arce, *"Linear Classifier with Reject Option for the Detection of Vocal Fold Paralysis and Vocal Fold Edema"* EURASIP Journal on Advances in Signal Prossessing, 2009.

[21] Kay Elemetrics. Voice and Speech Laboratory. Massachusetts Eye and Ear Infirmary, 1994.

APPENDIX – Files used

List of Normal Files used

Normal Voices	**Not used for**
LDP1NAL.NSP	
SLC1NAL.NSP	
DMA1NAL.NSP	
MXB1NAL.NSP	ATRI, Fatr
HBL1NAL.NSP	
DAJ1NAL.NSP	Fatr
JEG1NAL.NSP	
MCB1NAL.NSP	ATRI, Fatr
MXZ1NAL.NSP	ATRI, Fatr
AXH1NAL.NSP	ATRI, Fatr
JAN1NAL.NSP	ATRI, Fatr
LLA1NAL.NSP	
CAD1NAL.NSP	
JAF1NAL.NSP	
JTH1NAL.NSP	
EDC1NAL.NSP	Fatr
SCK1NAL.NSP	ATRI, Fatr
DFP1NAL.NSP	
SEB1NAL.NSP	
MAM1NAL.NSP	ATRI, Fatr
NJS1NAL.NSP	
SCT1NAL.NSP	ATRI, Fatr
JAP1NAL.NSP	
LAD1NAL.NSP	
PBD1NAL.NSP	
CEB1NAL.NSP	
JKR1NAL.NSP	
JXC1NAL.NSP	
LMV1NAL.NSP	ATRI, Fatr
VMC1NAL.NSP	
LMW1NAL.NSP	
BJV1NAL.NSP	
MJU1NAL.NSP	
FMB1NAL.NSP	
MFM1NAL.NSP	
OVK1NAL.NSP	
DWS1NAL.NSP	ATRI, Fatr
BJB1NAL.NSP	
PCA1NAL.NSP	
SIS1NAL.NSP	
DJG1NAL.NSP	
MAS1NAL.NSP	
SXV1NAL.NSP	
TXN1NAL.NSP	
WDK1NAL.NSP	ATRI, Fatr
GPC1NAL.NSP	
RHM1NAL.NSP	
EJC1NAL.NSP	ATRI, Fatr
JMC1NAL.NSP	
RJS1NAL.NSP	ATRI, Fatr
GZZ1NAL.NSP	
KAN1NAL.NSP	
RHG1NAL.NSP	

List of Pathological Files used

Pathologiocal Voices	**Not used for**
MXN24AN.NSP	
NJS06AN.NSP	ATRI, Fatr
SEC02AN.NSP	
TPP24AN.NSP	
LJH06AN.NSP	
LLM22AN.NSP	
TLP13AN.NSP	ATRI, Fatr
DBF18AN.NSP	
LAC02AN.NSP	
RJZ16AN.NSP	
WJB06AN.NSP	
KMC22AN.NSP	ATRI, Fatr
SWS04AN.NSP	ATRI, Fatr
GMS05AN.NSP	ATRI, Fatr
KMW05AN.NSP	ATRI, Fatr
SLC23AN.NSP	ATRI, Fatr
ESS05AN.NSP	ATRI, Fatr
MEC06AN.NSP	ATRI, Fatr
EED07AN.NSP	
SAV18AN.NSP	ATRI, Fatr
DMP04AN.NSP	
KAB03AN.NSP	ATRI, Fatr
LWR18AN.NSP	
LGM01AN.NSP	ATRI, Fatr
MEC28AN.NSP	
SAC10AN.NSP	ATRI, Fatr
SMA08AN.NSP	
LXC01AN.NSP	
MAB06AN.NSP	
SHD04AN.NSP	
JXF11AN.NSP	ATRI, Fatr
NMC22AN.NSP	
PMF03AN.NSP	
SAE01AN.NSP	
WCB24AN.NSP	
KAC07AN.NSP	
HLM24AN.NSP	
NML15AN.NSP	ATRI, Fatr
JEG29AN.NSP	
JLD24AN.NSP	
MCA07AN.NSP	
DMC03AN.NSP	ATRI, Fatr
EMP27AN.NSP	
JCR01AN.NSP	ATRI, Fatr
JMC18AN.NSP	
KCG23AN.NSP	
SBF11AN.NSP	
AXD19AN.NSP	ATRI, Fatr
KCG25AN.NSP	ATRI, Fatr
LVD28AN.NSP	
MCW21AN.NSP	ATRI, Fatr
VAW07AN.NSP	ATRI, Fatr, sAPQ, sPPQ
EAB27AN.NSP	
KTJ26AN.NSP	
LXC06AN.NSP	
MRC20AN.NSP	ATRI, Fatr
NMV07AN.NSP	ATRI, Fatr
TLS09AN.NSP	ATRI, Fatr
BSG13AN.NSP	
DSW14AN.NSP	
LAD13AN.NSP	
JPP27AN.NSP	
JXC21AN.NSP	
KDB23AN.NSP	

KLD26AN.NSP	ATRI, Fatr
LAP05AN.NSP	
MPS09AN.NSP	
NMB28AN.NSP	ATRI, Fatr
PLW14AN.NSP	
FMR17AN.NSP	ATRI, Fatr
JXD30AN.NSP	
KLC06AN.NSP	
KMS29AN.NSP	
KXB17AN.NSP	ATRI, Fatr
LBA15AN.NSP	
DRC15AN.NSP	
GMM09AN.NSP	ATRI, Fatr, sAPQ, sPPQ
GXL21AN.NSP	ATRI, Fatr
LBA24AN.NSP	
MAM08AN.NSP	
MFC20AN.NSP	
PMD25AN.NSP	
KLC09AN.NSP	
SLG05AN.NSP	ATRI, Fatr
CAK25AN.NSP	
MPB23AN.NSP	sAPQ, sPPQ
JCC10AN.NSP	
LAI04AN.NSP	ATRI, Fatr
NLC08AN.NSP	ATRI, Fatr
RMB07AN.NSP	
CAC10AN.NSP	ATRI, Fatr
DSC25AN.NSP	
NFG08AN.NSP	
RCC11AN.NSP	
AXT13AN.NSP	ATRI, Fatr
BAH13AN.NSP	
HJH07AN.NSP	ATRI, Fatr
LJS31AN.NSP	ATRI, Fatr
MXC10AN.NSP	ATRI, Fatr
EWW05AN.NSP	ATRI, Fatr
RXP02AN.NSP	
SEK06AN.NSP	
GSB11AN.NSP	
RJR15AN.NSP	ATRI, Fatr
BEF05AN.NSP	ATRI, Fatr
KJB19AN.NSP	
RXM15AN.NSP	
CMR26AN.NSP	
JLS11AN.NSP	ATRI, Fatr
SJD28AN.NSP	
LNC11AN.NSP	ATRI, Fatr
DAP17AN.NSP	
PAT10AN.NSP	
SEG18AN.NSP	
BKB13AN.NSP	
PGB16AN.NSP	ATRI, Fatr
CTB30AN.NSP	
LXR15AN.NSP	
TDH12AN.NSP	ATRI, Fatr
WXE04AN.NSP	
BLB03AN.NSP	
PMC26AN.NSP	
RWC23AN.NSP	
HXL58AN.NSP	
MWD28AN.NSP	ATRI, Fatr
BPF03AN.NSP	
LRD21AN.NSP	
NKR03AN.NSP	ATRI, Fatr
RTL17AN.NSP	
SCC15AN.NSP	
TPS16AN.NSP	ATRI, Fatr
DAS30AN.NSP	
EAS15AN.NSP	
JFN21AN.NSP	ATRI, Fatr
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SEF10AN.NSP	
MRB11AN.NSP	
PDO11AN.NSP	
JAP02AN.NSP	
KPS25AN.NSP	
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OAB28AN.NSP	
AOS21AN.NSP	
DWK04AN.NSP	
FXC12AN.NSP	ATRI, Fatr
EAS11AN.NSP	

JTM05AN.NSP	
RJL28AN.NSP	ATRI, Fatr
AMC14AN.NSP	ATRI, Fatr
MPF25AN.NSP	ATRI, Fatr
EJH24AN.NSP	
JRF30AN.NSP	
CRM12AN.NSP	
DVD19AN.NSP	
EEC04AN.NSP	
GDR15AN.NSP	ATRI, Fatr
RJF22AN.NSP	
GXT10AN.NSP	ATRI, Fatr
HXI29AN.NSP	
JHW29AN.NSP	ATRI, Fatr
CMA06AN.NSP	
WFC07AN.NSP	
WST20AN.NSP	
ALB18AN.NSP	
RPJ15AN.NSP	
RPQ20AN.NSP	
WJP20AN.NSP	
CLS31AN.NSP	