# ON-TALK AND OFF-TALK DETECTION: A DISCRETE WAVELET TRANSFORM ANALYSIS OF ELECTROENCEPHALOGRAM

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## ABSTRACT

Spoken interaction with a machine results in a behaviour that is not very common in face-to-face human communication: *Off-Talk*, which is defined as speech utterances that are not directed to an immediate interlocutor, the machine, but to another person or even oneself. It is our contention that a system which is able to detect the *Off-Talk* utterances can interact with a human in a more efficient manner by acknowledging that the utterances are not directed to the system and hence, not replying to *Off-Talk* utterances. In this paper, we demonstrate the discrimination power of a wide range of Electroencephalogram (EEG) frequency bands using wavelet transform analysis and propose models for *On-Talk* and *Off-Talk* detection using audio and EEG signals, and their fusion. Our study shows that the EEG signal can identify the occurrence of *Off-Talk* utterances with promising accuracy and its fusion with audio features adds a slight improvement in these results.

***Index Terms***— multimodal interaction, dialogue system, brain-computer interface (BCI), electroencephalogram (EEG), on-off talk (speech) detection, multi-sensor fusion

## 1. INTRODUCTION

It has been observed that when people interact with computer systems, not only do they talk to the computer system but also, they tend to talk to themselves and to other people if present [1, 2, 3]. Oppermann et al [1] coined the term "*Off-Talk*" to denote speech that is not addressed to the computer system, as opposed to utterances that are directed to it, and therefore need to be understood by the system as "*On-Talk*". Batliner et al [2] open their paper with an example from Shakespeare's *Hamlet*, where Hamlet seems to change his speaking style when addressing his interlocutor to utterances that are spoken, but not directed towards his interlocutor. It shows that this is not a new phenomena, but part of human nature that Shakespeare expressed with his characters [2]. The definition of *Off-Talk*, as provided by Oppermann et al [1, p. 1] encompasses every utterance that is not directed to the system, such as: (i) soliloquy/thinking aloud, (ii) swearing, (iii) reading from displayed text aloud, (iv) conversation with other person(s) present, (v) telephone conversation (e.g., with cellular phone) and (vi) extrinsic speech (e.g., video player, TV set, etc.). The objective of this paper is to model *On-Talk* and *Off-Talk* in terms of EEG and audio features.

Previous studies by Oppermann et al [1] report that the loudness difference between *On-Talk* and *Off-Talk* can be used as a significant indicator of *Off-Talk* and Hayakawa et al [3] also suggest that the prosodic features can help the *On-Talk* and *Off-Talk* detection. One of the contributions of the present study is the demonstration of discrimination power of EEG frequency bands for *On-Talk* and *Off-Talk* detection.

The EEG signal and its different frequency bands have been employed in some applications, such as seizure detection, emotion recognition, and even speech recognition. Ocak [4] analyses the frequency bands between 0 Hz – 86.8 Hz using wavelet transform, and reports that the higher bands between 43.4 Hz – 86.8 Hz provides the optimum accuracy for detection of epileptic seizures. Adeli et al [5] use a wavelet chaos methodology to detect seizure using EEGs and EEG sub-bands and analyse EEG signals between 0 Hz – 60 Hz. Petrantonakis et al [6] use the lower frequency bands between 8 Hz – 12 Hz and 13 Hz – 30 Hz for emotion recognition. The EEG signal has also been used for the speech recognition of unspoken words where Porbadnigk et al [7] recorded the 16 EEG signal channels with a 128 cap montage and recognised five words with an average accuracy of 45.50%. The most prominent band of the EEG signal lies in the lower frequencies (Alpha band for attentional demands and Beta band for emotional and cognitive processes) [8], but these bands may contain noise of muscle activity which makes it difficult to measure only neuronal activity in the bands during speech articulation, as speech articulation results in muscle activities. Muscle activity can introduce noise in EEG signals (e.g., peak frequency of masseter muscles movements are in 50 Hz – 60 Hz range, and frontalis muscles movements are between 30 Hz – 40 Hz), and the noise band limit is between 15 Hz – 100 Hz [9]. Kumar et al [10] also report a noise range for frontalis muscles between 20 Hz –

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30 Hz and temporal muscles between 40 Hz – 80 Hz. Posterior head muscle movements have a higher peak frequency close to 100 Hz, but this depends on many factors (e.g., sex, force and direction of contraction, etc.) [10]. Muscle activity may introduce artefacts in the EEG signal in a frequency range (≈20 Hz – 300 Hz) where the most artefacts are at the lower end [11]. However, the use of physiological signals (including the EEG signal) for speech related task in noisy and competing speech environment is well recognised. For removing the talk related muscle artefacts from EEG, heavy low pass signal filtering (frequencies above 10 Hz – 12 Hz should be filtered) can be used [12].

It is claimed that the right hemisphere of the brain is largely responsible for the speech prosodic characteristics [13, 14, 15] and Heart Rate (HR) and Skin Conductance (SC) also help in predicting the cognitive states [16], emotions [17], and *On-Talk* and *Off-Talk* [3]. From the literature as stated above, we conclude three things: (i) First, the prosodic characteristics are different for *On-Talk* and *Off-Talk*, (ii) Second, the right hemisphere of the brain largely determines the speech prosodic characteristics, and (iii) Third, the EEG signal is full of artefacts while someone is speaking, but the artefacts' range is between 15 Hz – 300 Hz, and there are still some frequencies $< 15$ Hz which are not sensitive to muscle artefacts and contain the neural activity. Moreover, the skull EEG electrodes are unable to record the frequencies above 40 Hz according to clinical standards. We note that, while contrary to a common misconception the human skull does not filter out higher frequencies [18], neural activity at such frequencies is harder to detect due attenuation caused by the skull's resistivity and the distance between the small generator and EEG electrode [19]. That is why this study assumes that the frequencies above 40 Hz contain only muscle artefacts, providing an opportunity to demonstrate the effect of muscle artefacts in the EEG signal for *On-Talk* and *Off-Talk* detection. Therefore, we analysed the full frequency band (0 Hz – 512 Hz) using Discrete Wavelet Transform (DWT) analysis to explore both the neural activity and muscle artefacts for *On-Talk* and *Off-Talk* detection.

## 2. DATA SET

The data from the ILMT-s2s corpus[1] was used for this paper due to the availability of finely time-stamped audio and physiological signals (EEG, heart rate and skin conductance) and also to use the results of Hayakawa et al [3] as a reference to determine the degree of any improvement.

**The ILMT-s2s corpus:** The corpus consists of 15 dialogues of English speakers communicating with Portuguese speakers to perform the HCRC Edinburgh Map Task [20], a task where the subject is to guide the interlocutor along a predefined route on the map of one of the subjects. The subjects are situated in different rooms and communicate in their mother tongue to their interlocutor using a Speech-to-Speech Machine Translation (S2S-MT) system that Hayakawa et al [21] call the *ILMT-s2s System*. The corpus consists of ≈9.5 hours of audio, video and biological signal recordings of interlingual system mediated communication of 15 subject pairs (15 English and 15 Portuguese speakers).

**The ILMT-s2s System:** The S2S-MT system uses a 'Push-to-Talk' button to activate transactions, with each subject's voice being used only as an input and not transmitted to the interlocutor. The subject's utterance is automatically converted into text (ASR), machine translated and then the translated text is sent to the interlocutor's computer to be output using Text-to-Speech (TTS), speech synthesis. Aside from the synthesised speech output, the ASR result is displayed on the subject's computer and the TTS text is displayed on the interlocutor's computer.

**Audio and Video Recordings:** Each dialogue recording consists of two audio and five video channels of data, but for this study, the audio of the whole dialogue that was captured by the 2 main video cameras was used.

**Biosignal Recording:** The corpus contains recordings of Heart Rate (HR) using the Blood-Volume Pulse (BVP) sensor, Skin Conductance (SC) and Electroencephalography (EGG) collected using a Mind Media B.V., Nexus-4 from one subject of the dialogue pair. The BVP sensor placed on the index finger, with the SC sensor put on the middle and ring finger. The EEG sensors are placed in the F4, C4, P4 (right hemisphere of the brain that is responsible for the control of speech prosody [13, 14, 15]) with a ground channel placed at A1 (as depicted in Figure 1) of the 10 – 20 location system [22]. The sampling frequencies for the SC, HR and EEG are 32 kHz, 32 kHz and 1,024 kHz respectively.

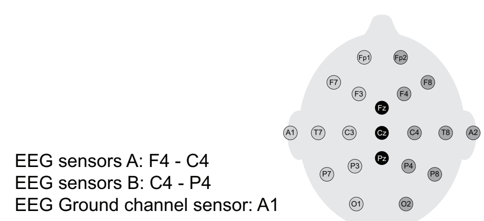



**Fig. 1**: 10 – 20 system layout map

**Annotation of *On-Talk* and *Off-Talk*:** Since the ILMT-s2s System uses a 'Push-to-Talk' activation system, subject utterances that activated the S2S-MT system are considered as *On-Talk* and all other utterances are labelled as *Off-Talk*. Of the 1,681 transcribed utterances, 1,127 (≈67.0%) are labelled as *On-Talk* and 554 (≈33.0%) are labelled as *Off-Talk*.

[1]ISLRN: 100-610-774-625-0.

## 3. EEG SIGNAL DECOMPOSITION

The EEG signal ($S$) is decomposed into 11 components using the Discrete Wavelet Transform (DWT) using MATLAB,[2] where $S = d1 + d2 + d3 + \ldots + d10 + a10$ as depicted in Figure 2. The DWT helps us in evaluating the discrimination power of each component ($d1, d2$ etc) for the *On-Talk* – *Off-Talk* prediction.

## 4. FEATURE EXTRACTION

The following features are used for the classification task.

**Audio features:** We use openSMILE [23] to extract the acoustic features that have been widely used for emotion and spoken expression recognition [24]. The acoustic feature set contains the MFCC, voice quality, fundamental frequency ($F0$), $F0$ envelope, LSP and intensity features along with their first and second order derivatives. However, many statistical functions are also applied to the features which resulted in-total of 988 features for every speech segment. The motivation behind using this feature set is to model the differences in spoken expressions for *On-Talk* and *Off-Talk* detection.

**Physiological features:** For each annotated label we have extracted the Shannon Entropy, mean, std, mode, min, max, median, energy, power, minimum ratio and maximum ratio along with their first and second order derivatives. As a result, we have 66 features for each component (e.g., $d1, d2$); 33 for sensor A, and 33 for Sensor B (Figure 1) and in total, 726 EEG features for each annotated label.

## 5. CLASSIFICATION METHODS

We investigated the automatic detection of '*On-Talk* and *Off-Talk* utterances' using four machine learning methods, namely Linear Discrimination Analysis (LDA), Nearest Neighbour (KNN with $K$=15), Decision Trees (DT) and Random Forest (RF). These classifiers are employed in MATLAB using the statistics and machine learning toolbox but the RF classifier is employed in python using the scikit-learn library.[3] LDA works by assuming that the feature sets of the classes to be discerned are drawn from different Gaussian distributions and adopting a pseudo-linear discriminant analysis (i.e., using the pseudo-inverse of the covariance matrix [25]). KNN and DT are non-parametric methods.

## 6. RESULTS AND DISCUSSION

We conducted an experiment using different EEG frequency bands and acoustic features. We assessed the results using the $A$-weighted $F$-score statistic (with the $\beta$ parameter set to 1). In this setting, the $A$-weighted $F$-score is equivalent to the averaged harmonic mean of both classes which results in a baseline of 50% for the classification task. The classification results of the 1,127 *On-Talk* and 554 *Off-Talk* utterances are reported in Table 1.

**Table 1**: 10-fold cross validation results ($A$-weighted $F$-score %) for *On-Talk* – *Off-Talk* detection. (Baseline is 50%)

| Results | | LDA | KNN | DT | RF |
|---|---|---|---|---|---|
| $d1$: | (256 Hz – 512 Hz) | 67.53 | 65.64 | 65.92 | **72.01** |
| $d2$: | (128 Hz – 256 Hz) | 65.59 | 65.87 | 62.24 | **68.77** |
| $d3$: | (64 Hz – 128 Hz) | 65.24 | 64.11 | 61.41 | 67.70 |
| $d4$: | (32 Hz – 64 Hz) | 59.10 | 56.30 | 59.49 | 63.11 |
| $d5$: | (16 Hz – 32 Hz) | 55.11 | 55.63 | 59.01 | 61.51 |
| $d6$: | (8 Hz – 16 Hz) | 57.55 | 56.11 | 59.05 | 62.93 |
| $d7$: | (4 Hz – 8 Hz) | 58.64 | 54.33 | 55.40 | 60.54 |
| $d8$: | (2 Hz – 4 Hz) | 58.36 | 51.45 | 59.19 | 61.86 |
| $d9$: | (1 Hz – 2 Hz) | 55.46 | 52.28 | 55.78 | 62.67 |
| $d10$: | (0.5 Hz – 1 Hz) | 56.02 | 44.64 | 55.37 | 60.20 |
| $a10$: | (0 Hz – 0.5 Hz) | 56.32 | 64.03 | 70.76 | **74.80** |
| | Audio | 82.73 | 67.91 | 84.14 | **91.36** |
| | Audio + $d1$ | 82.63 | 65.98 | 83.62 | ***92.08*** |
| | Audio + $a10$ | 80.34 | 68.74 | 82.15 | 91.45 |

Of the four classification methods, the results indicate that the Random Forest (RF) classifier provides the best results in all tested settings. The highest frequency band ($d1$) achieved an $A$-weighted $F$-score of 72.19%, and the second highest frequency band ($d2$) provides an $A$-weighted $F$-score of 68.77%. The reason why results are better using high EEG frequency bands is probably that these frequencies are reflecting speech related muscle artefacts in the recorded EEG signal, as explained in section 1. The EEG frequencies ($> 15$ Hz and $< 40$ Hz) contains muscle artefacts and neural activities, and able to detect the *On-Talk* and *Off-Talk*. The lowest frequency band $a10$ produced the best results (74.80%) for the classification task which may be due to the fact that the right hemisphere of human brain is responsible for speech prosody and that prosodic information may be encoded in lower bands of the EEG signal because the lower bands $< 15$ Hz do not contain the muscle artefacts, as explained in section 1. The audio features set provides the best classification results (91.36%), and the fusion of audio and EEG features ($d1$) improves the performance slightly (92.08%). We draw a Venn digram to explore the mutual information of the top three results which are obtained using $d1$, $a10$ and the Audio signal as depicted in Figure 3, and the confusion matrix of this figure is listed in Table 2.

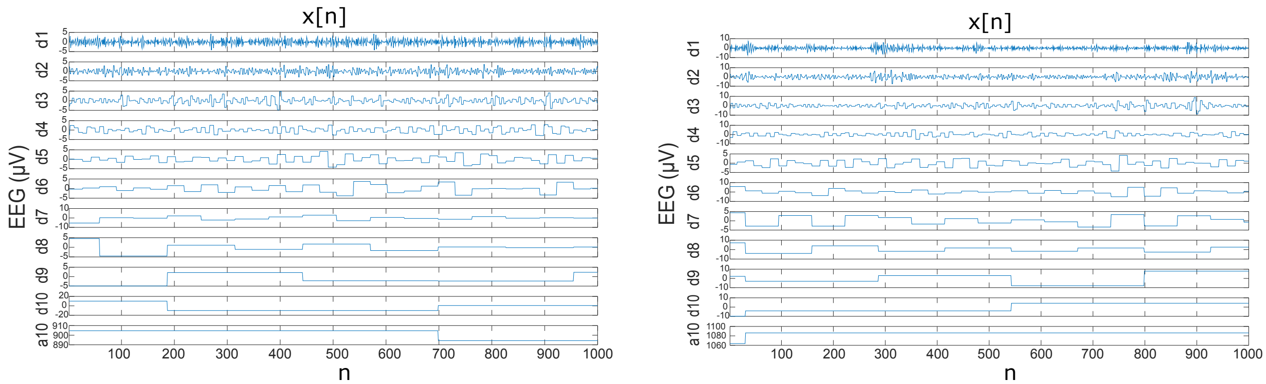
**Table 2**: Confusion Matrix of the top three best results, showing classification of instances

| | $a10$ | | $d1$ | | Audio | |
|---|---|---|---|---|---|---|
| | *Off-T.* | *On-T.* | *Off-T.* | *On-T.* | *Off-T.* | *On-T.* |
| *Off-Talk* | 365 | 189 | 308 | 246 | 457 | 97 |
| *On-Talk* | 103 | 1,024 | 150 | 977 | 27 | 1,100 |

In Figure 3, the 'blue circle (Target)' represents the anno-

[2] http://uk.mathworks.com/products/matlab/ – last verified 10/2017

[3] http://scikit-learn.org/stable/ – last verified 10/2017




(a) EEG epoch during off talk

(b) EEG epoch during on talk

**Fig. 2**: A wavelet decomposition of the EEG signal ($S$) into 11 components ($d1, d2, \ldots, a10$) where $S = d1 + d2 + \ldots + a10$

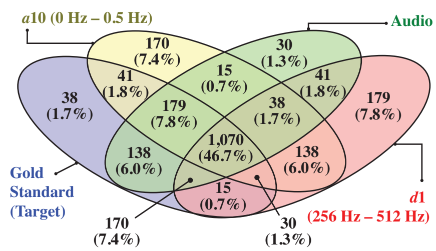



**Fig. 3**: Mutual Information: Venn diagram of the results

tated labels, the 'yellow circle' represents the predicted labels by the features of $a10$ frequency band using the RF classifier, the 'green circle' represents the predicted labels by the acoustic features using the RF classifier, and finally the 'red circle' represents the predicted labels by the features of $a10$ frequency band using the RF classifier. From the Venn diagrams overlap, it is observed that there are 38 instances (8 *On-Talk* and 30 *Off-Talk*) which have not been recognised by any of the feature sets. However there are 1,070 instances (875 *On-Talk* and 195 *Off-Talk*) which have been detected by all three feature sets. The EEG features provide less accurate results than audio features but are able to capture some information (41 (yellow circle: $a10$), 30 (overlap of yellow: $a10$ and red circles: $d1$) and 15 (red circle: $d1$) instances) which is not captured by the audio features as depicted in Figure 3.

We have also conducted a mid-$p$-value McNemar test to compare the results of $a10$, $d1$ and Audio features with a null hypothesis which is that $a10$, $d1$ and Audio features have equal accuracy for predicting the target (*On-Talk* – *Off-Talk* detection). The test rejects the null hypothesis for 'Audio and $a10$' ($p_{Audio-a10} = 1.67\text{e}{-36}$), and 'Audio and $d1$' ($p_{Audio-d1} = 9.44\text{e}{-52}$) but fails to reject the null hypothesis for '$a10$ and $d1$' ($p_{a10-d1} = 0.08$). High-frequency bands ($>40$ Hz e.g., $d1$) provide good results, and due to the muscle activity they capture, we can confirm that the *On-Talk* and *Off-Talk* utterances have a different muscle activity pattern. In addition, we also obtain good results from the $\{a10\ (0\,\text{Hz} – 0.5\,\text{Hz})\}$ band which has robustness against muscle activities, which indicates that *On-Talk* and *Off-Talk* utterances also have different neural activity patterns.

In a previous study, Hayakawa et al [3] explored the EEG Gamma band along with SC, HR and acoustic features for the detection of *On-Talk* and *Off-Talk* and reported an $A$-weighted $F$-scores of 57.19% when using only the EEG Gamma band. Our results of the wavelet analysis of the EEG signals significantly improves the performance for *On-Talk* and *Off-Talk* detection up to 74.80%. The acoustic features provide the best results for *On-Talk* and *Off-Talk* detection in this study and in the results from Hayakawa et al [3]. However, the results from Hayakawa et al [3] do not provide promising results using physiological signals alone and used more acoustic features (6,371 acoustic features) than those used in the method (988 acoustic features) reported in this paper. In the previous study Hayakawa et al [3] only present an idea of detecting *On-Talk* and *Off-Talk* using different modalities (e.g., EEG gamma band, audio) instead of demonstrating and evaluating the results in detail, which this study covers.

## 7. CONCLUSION

The lowest frequency band $\{a10\ (0\,\text{Hz} – 0.5\,\text{Hz})\}$ of the EEG signal provides more accurate result than other frequency bands, and audio features provide the best results. The high frequencies reflect muscle artefacts, and the results indicate that high frequency ($>40$ Hz) bands of the EEG signal contribute significantly towards the detection of *On-Talk* and *Off-Talk* utterances. Hence, the muscle artefacts in the EEG signal have a positive influence towards the detection of *On-Talk* and *Off-Talk*. A possible direction of future work is to explore muscle movements during *On-Talk* and *Off-Talk* using visual and Electromyography (EMG) signals. Another possible future work is to investigate the EEG signal while someone is planning to press the button or planning to speak.

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