A SIMPLE CORRELATION-BASED MODEL OF INTELLIGIBILITY FOR NONLINEAR SPEECH ENHANCEMENT AND SEPARATION

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ABSTRACT

Applying a binary mask to a pure noise signal can result in speech that is highly intelligible, despite the absence of any of the target speech signal. Therefore, to estimate the intelligibility benefit of highly nonlinear speech enhancement techniques, we contend that SNR is not useful; instead we propose a measure based on the similarity between the time-varying spectral envelopes of target speech and system output, as measured by correlation. As with previous correlation-based intelligibility measures, our system can broadly match subjective intelligibility for a range of enhanced signals. Our system, however, is notably simpler and we explain the practical motivation behind each stage. This measure, freely available as a small Matlab implementation, can provide a more meaningful evaluation measure for nonlinear speech enhancement systems, as well as providing a transparent objective function for the optimization of such systems.

1. INTRODUCTION

Speech enhancement concerns taking a target speech signal that has been corrupted, by the addition of interfering sources and transmission through an acoustic channel, and mitigating the impact of these corruptions. Enhancement can have two distinct goals: improving quality, which relates to how “clear” or “natural” the enhanced speech sounds, and improving intelligibility, which focuses on the more practical problem of whether a listener can understand the message in the original target speech. Although we might expect that quality and intelligibility are strongly correlated, there are ample situations in which speech of relatively low quality can nonetheless achieve high intelligibility \cite{16, 21}, and where improving quality does not necessarily improve intelligibility \cite{9}.

In this paper we ignore quality (and related effects such as listener fatigue) and concentrate on intelligibility. We focus specifically on time-frequency masking algorithms, which have been widely used in automatic speech recognition \cite{6}, computational auditory scene analysis \cite{20}, noise reduction \cite{14, 2}, and source separation \cite{22, 15}. In this type of algorithm, a time-varying and frequency-dependent gain is applied across a number of frequency channels. In some variants, the gains are quantized to zero or one, giving a binary masking algorithm where the pattern of gains is referred to as the binary mask. One type of binary mask -- the ideal binary mask (IBM) -- has shown to be able to increase speech intelligibility significantly \cite{3, 2, 13}. This mask is 'ideal' in that it relies on perfect knowledge of both clean target and interference prior to mixing, and is constructed to pass only those time-frequency cells in which the target energy exceeds the interference. An intriguing property of the IBM is that applying such a mask to a sound consisting only of noise results in high intelligibility for the speech upon which the mask was based \cite{21, 12}, even though the perceived quality of the reconstructed speech is very poor: depending on the resolution of the time-frequency distribution, it will have no pitch or other fine structure, and fine nuances of energy modulation are lost. Similar characteristics are found to those of noise-excited channel-vocoded speech \cite{16}. An attempt to measure the signal to noise ratio (SNR) in such signals would find no trace of the original target in the final output, so SNR-based measures will not be a useful basis for accounting for this intelligibility. What is preserved, however, is the broad envelope in time and frequency. This suggests that an intelligibility estimate could be developed based on the similarity of this envelope between target speech and system output.

In this paper, we use correlation as a measure of similarity between time-frequency envelopes of target and enhanced speech. Given this basic principle, we make a number of design choices and system enhancements with a view to matching the general properties of observed subjective intelligibility of nonlinearly-enhanced signals. At each stage, we strive for the simplest and most transparent processing that can effectively match the subjective results. Our outcome is a simple correlation-based measure that can predict intelligibility with approximately the same fidelity as more complex models based on far more detailed models of auditory processing \cite{4}. We feel this simplicity and transparency is a considerable advantage as a guide for developing enhancement systems.

2. NORMALIZED SUBBAND ENVELOPE CORRELATION

To estimate intelligibility, the correlation between the time-frequency representations of the target (reference) and the output of the time-frequency masking algorithm is calculated:

\[
\sum_{\tau} \sum_{k} T(\tau, k) \cdot Y(\tau, k),
\]

where \(\tau\) the time index, \(k\) the frequency index, \(T(\tau, k)\) is the energy envelope of the target signal, and \(Y(\tau, k)\) is the energy envelope of the output. This correlation will not have an upper bound, and in low energy regions of \(T(\tau, k)\) the inclusion of potential unwanted energy in \(Y(\tau, k)\) will have a very small impact on the correlation. To improve this behavior, we normalize with the Frobenius norm of \(T(\tau, k)\) and \(Y(\tau, k)\) and refer to this measure as the normalized subband envelope correlation (nSec):

\[
n\text{Sec} = \sum_{\tau} \sum_{k} \frac{T(\tau, k) \cdot Y(\tau, k)}{||T(\tau, k)|| ||Y(\tau, k)||}
\]

3. EXPERIMENTAL DATA

To verify that nSec is a useful measure of speech intelligibility, we use the results from Kjems et al. \cite{12}, where speech intelligibility of IBM-masked noisy speech is measured using normal hearing subjects, three SNR levels, four noise types, and different local SNR criterions (LC). LC is the threshold used to construct the IBM; a
larger LC results in an IBM with proportionally fewer nonzero values:

\[
\text{IBM}(\tau, k) = \begin{cases} 
1, & \frac{T(\tau, k)}{N(\tau, k)} > \text{LC} \\
0, & \text{otherwise} 
\end{cases}
\]

where \(N(\tau, k)\) is the energy envelope of the noise signal.

Two of the three SNR levels used in the experiments by Kjems et al. were set to 20% and 50% intelligibility of the speech and noise mixtures with no binary masking. The third SNR level was fixed at -60 dB to examine the effect of applying the IBM to pure noise. Four different noise conditions were used: speech shaped noise (SSN), cafeteria noise, car interior noise with mainly low-frequency energy, and noise from a bottling hall with mainly high-frequency energy. The LC values resulted in IBMs consisting of between 1.5% and 80% of nonzero cells, and an all-one mask (aom) was used to measure the intelligibility of the unprocessed mixture with no binary masking. A 64 channel Gammatone filterbank with centerfrequencies from 55 Hz to 7742 Hz equally spaced on the ERB (equivalent rectangular bandwidth) scale was used, and the output was divided into 20 ms frames with 10 ms overlap. The results are shown with dotted lines and hollow symbols in Figure 1 (and are repeated in subsequent figures). To align the results, they are plotted as a function of the RC value defined as \(\text{RC} = \text{LC} - \text{SNR}\ [\text{dB}]\). The results are shown with solid lines and filled symbols in Figure 1.

Looking at Figure 1, it can be seen that even though the nSec is not aligned with the subjective listening tests, the overall shape and behavior is encouraging: Increasing SNR gives a better or similar nSec, and a distinct peak in correlation as a function of RC value is seen at all curves expect for the -60 dB SNR cafeteria noise (Fig.1.B). If this curve had been continued to higher RC values, it would have made a peak at some point, because higher RC values makes the binary mask more sparse with fewer ones, and, ultimately, \(\text{Y}(\tau, k)\) will be zero. At the other extreme, at low RC values, the nSec levels off which is most evident from Figure 1.A and 1.D. The reason is that at some RC value, the time-frequency units added to \(\text{Y}(\tau, k)\) by lowering the RC value will not change the numerator of Equation 2 because no energy is found at these time-frequency units in \(T(\tau, k)\). At the same time, the denominator will continue to increase as the RC value decreases, due only to the added energy in \(|Y(\tau, k)|\): \(|T(\tau, k)|\) is a fixed value independent of SNR and RC value.

Comparing the three SNR levels, it can be seen that the peak of the nSec shifts towards lower RC values for higher SNRs – a reasonable property, if we recognize that the IBM for a certain target and noise sound is a function of the RC value only, and that increasing SNR level implies that the RC value can be lowered without increasing the number of noise-dominated time-frequency units in the binary masked mixture. At increasing SNR levels, the RC value is lowered by increasing the LC value with less than the increase in SNR level.

The nSec for the speech shaped noise (Fig.1.D) with an all-one mask is considerably higher at all three SNR levels compared to other noise types. The nSec of the -60 dB SNR mixture with an all-one mask is approximately 0.4, despite the fact that practically no target sound is found in the mixture. Two random signals always will give a positive correlation as long as they contain energy in some of the same time-frequency regions, and the speech shaped noise do, since it was made by superimposing 30 sequences of the speech from the corpus with random silence durations and starting times [19].

The last observation we make of the unmodified nSec is that the location of the peaks are at higher RC values compared to the subjective listening tests. This property is caused by the fact that
nSec is decreased when \( Y(\tau, k) \) contains energy in the low energy regions of \( T(\tau, k) \); to get a high nSec, the binary mask should only present the high energy regions of \( T(\tau, k) \).

To improve the alignment between the subjective listening tests and the nSec, the following modifications are introduced:

### 4.1 Frequency Normalization

In speech signals, high frequencies have less energy than low frequencies, but this difference does not reflect the frequencies’ importance to intelligibility. Using the nSec without any frequency normalization will make the low frequencies dominate the result. Furthermore, the auditory system can to some degree adapt to the listening situation and a minor fixed coloration of the speech spectrum is not expected to affect intelligibility. To compensate for the difference in energy and any fixed colorations, we normalize the frequency channels to equal energy. This normalization has the drawback that at increasing RC values, when the binary mask becomes more sparse, some frequency channels will contain few non-zero elements, which would become very large because of the normalization. To avoid these high level time-frequency units, amplitude compression should follow the normalization (although in frequency channels with no non-zero elements, no normalization should be applied).

### 4.2 Compression

To decrease the relative importance of high level time-frequency units mainly produced by the frequency normalization, compression can be applied to \( T(\tau, k) \) and \( Y(\tau, k) \). Compression will move the peaks of the nSec curves towards lower RC values, but also reduces the difference between the three SNR levels. To align the nSec peaks with the subjective listening tests, \( T(\tau, k) \) and \( Y(\tau, k) \) are raised to the power of 0.15.

### 4.3 DC removal

As previously stated, the nSec will be positive even if two random signals are used because their energy is always positive. To reduce this offset in the time-frequency representations, each frequency channel should be high-pass filtered. This high-pass filtering will push the values down to zero in the case where we have flat, but nonzero, energy and emphasize changes in energy instead of absolute levels. The used high-pass filter has a single zero at 1 and a single pole at 0.95.

![Figure 2: The modified nSec with frequency normalization, compression, and DC removal compared to the subjective listening tests.](image-url)

### 5. RESULT

As seen in Figure 2, the modifications improve the correspondence between the subjective listening test and the nSec. The differences are most pronounced at low and high RC values where the slope of the modified nSec is too shallow, and in the unprocessed condition (aom) the results are too low and too closely placed in the bottling hall and cafeteria noise condition. Ideally, the three SNR levels should give a intelligibility of 50%, 20% and 0%, but the compression, which was introduced to shift the peaks of the nSec towards lower RC values, also compresses the results at low RC values, making them more equal. At high RC values the shallow slope of the modified nSec is also a outcome from using compression. Compression increases the impact of low-amplitude time-frequency units and a more sparse mask is needed to reduce the nSec.

To allow some nonlinearity in the relationship between the nSec and speech intelligibility, a logistic function can be applied:

\[
p(\epsilon) = \frac{1}{1 + e^{(\epsilon - \phi)/s}},
\]

where \( \phi \) is the offset, and \( s \) is the slope of the logistic function [4]. To find the offset and slope we use the unconstrained nonlinear minimization function fminsarch in Matlab to minimize the squared error between nSec and the results from the subjective listening test using speech shaped noise. The found offset and slope of \( \phi = 0.62 \) and \( s = 0.09 \) are used to transform the nSec results from Figure 2 into the results seen in Figure 3. The overall performance is improved: a better correspondence between the subjective listening tests and the nSec is seen, but this is achieved at the expense of the match in the situation with no binary masking (aom).

### 6. DISCUSSION

Our proposed method uses a different approach compared to intelligibility measures as AI, SII, and STI [1, 7, 18] by using the correlation as the fundamental function for measuring intelligibility. In the AI, SII, and STI, the intelligibility is measured as a sum and weighting of SNR in a number of frequency channel. A more similar approach to ours are used in [10] for measuring speech quality and in [4] to measure intelligibility. In both works, the cross-correlation coefficient is used to measure the similarity between internal representations of the target and test signal. The internal representations are patterns of the neural activity at some level in the auditory system and are based on complex auditory models. Besides
The use of internal representation, Christiansen et al. [4] makes an interesting difference from our approach by calculating the cross-correlation coefficient in short time frames and sorting them in low, medium, and high level correlation frames. The correlation frames has a length of 20 ms with 50% overlap, but only the high level correlation frames are used in the model output which is mapped to intelligibility using a logistic function equal to Equation 4.

The model by Christiansen et al. shows significant improvements compared to the speech-based coherence SII method [11] and the speech-based STI method [8], when using the same subjective intelligibility using a logistic function equal to Equation 4.

It is of interest to compare our approach and results with the model by Christiansen et al., but concluding which one is better is not appropriate from the results shown in Figure 3 and 4. Mainly because the logistic function used in Figure 3 was fitted directly to the subjective results using the speech shaped noise condition, whereas the logistic function used by Christiansen et al. was fitted to the psychometric curves from subjective listening tests of unprocessed mixtures at different SNR levels. The consequence of this difference is evident using the all-one mask, where the results from the nSec are too close and too low, which is not the case for the model by Christiansen et al. An interesting difference between the two methods is the bottling hall noise, where the nSec, although very similar at the three SNR levels, has a better alignment of the peaks, which is caused by the frequency normalization as explained in section 4.1.

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We might question whether the proposed modifications of the nSec are the correct ones to use, and if they appear in the correct order. The modifications could be compared to processing steps in the auditory system, but in this case we have selected and ordered them purely to adjust the nSec to the subjective results and not to simulate specific aspects of the auditory system. Similarly, the use of the correlation as underlying basis was supported by the preliminary results seen in Figure 1, and not by assumptions about correlation being used at some level in human perception. Introducing additional steps – simple or complicated – could potentially improve the precision of the method, but would also introduce additional processing and parameters that would make the system less transparent for the user.

Another approach to measure intelligibility is the use of automatic speech recognition systems, where the number of correctly identified words or phonemes are used as a measure of speech intelligibility. This method has shown promising results [17, 5], but it is vulnerable to peculiarities of speech recognition systems that can make them differ widely from the perception of listeners. Trivial mismatch between the processed signals and the training data used by the recognizer can result in misleading low results.

A straightforward approach to evaluate time-frequency masking algorithms is to count the number of errors in the binary mask. Although we believe that the binary mask itself can explain a large amount of the intelligibility, this approach has various drawbacks e.g. the type of errors can have widely differing impact [14], the location of errors is important, and it is not certain which type of binary mask should be used as reference. Furthermore, this approach will not show the difference between applying the same binary mask to mixtures at different SNR levels.

The nSec has shown a fine agreement with subjective listening test of the IBM applied to different mixtures and SNR levels, but this is only one of many methods of time-frequency masking. In the present work, we have not examined how the nSec will behave using e.g. non-binary masks – the general case of applying a time-varying gain in a number of frequency bands – but we are hopeful that it will continue to agree with human performance. We note that the nSec can fail if the target and system output become misaligned e.g. if the processed mixture is delayed compared to the target, however this could be accommodated by searching over a timing skew parameter (full cross-correlation).

7. CONCLUSION

By focusing on the correlation between the broad spectral envelope of target and system output, while completely ignoring the fine structure, we arrive at an intelligibility measure able to match a range of subjective results that would be very difficult to explain by SNR measures. We therefore suggest that future work on nonlinear speech enhancement, if it is concerned with intelligibility, should use measures based on correlation in place of SNR. To this end, we have released a simple drop-in implementation of our measure, written in Matlab1.

1See http://labrosa.ee.columbia.edu/projects/intelligibility/
Although there are other, existing intelligibility measures that are able to match subjective data as closely as ours, our measure is constructed to be as simple as possible, with a consequent benefits in terms of transparency and diagnosis: when a system performs poorly under this measure, it is relatively easy to look at the processed envelopes going into the final correlation to see in which regions they are most different, thereby suggesting where to look for improvements. We hope that measures of this kind can help to focus and promote progress in speech intelligibility enhancement systems.

REFERENCES

Figure 4: The predicted intelligibility using the model by Christiansen et al. [4] compared to the subjective listening test.