SUS-based Method for Speech Reception Threshold Measurement in French

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Abstract
We propose a new method for measuring the threshold of 50% sentence intelligibility in noisy or multi-source speech communication situations (Speech Reception Threshold, SRT). Our SRT-test complements those available e.g. for English, German, Dutch, Swedish and Finnish by a French test method. The approach we take is based on semantically unpredictable sentences (SUS), which can principally be created for various languages. This way, the proposed method enables better cross-language comparisons of intelligibility tests. As a starting point for the French language, a set of 288 sentences (24 lists of 12 sentences each) was created. Each of the 24 lists is optimized for homogeneity in terms of phoneme-distribution as compared to average French, and for word occurrence frequency of the employed monosyllabic keywords as derived from French language databases. Based on the optimized text material, a speech target sentence database has been recorded with a trained speaker. A test calibration was carried out to yield uniform measurement results over the set of target sentences. First intelligibility measurements show good reliability of the method.

1. Introduction
For studying human speech perception performance in noisy environments, intelligibility threshold measurements are often used. They allow the performance differences between a large number of acoustical conditions to be expressed in a compact manner. For example, advantages related to certain configurations, such as the spatial unmasking enabled when switching from monaural to binaural hearing, can be quantified in a sensitive way (Bronkhorst, 2000). Another application domain is that of relative speech quality assessment, where the intelligibility threshold can serve as a quality measure. The sensitive measurement is achieved based on the steep psychometric function of speech identification in noise. For the 50% intelligibility threshold, the so-called speech reception threshold (SRT), slopes between 10 and 20% per dB signal-to-noise ratio (SNR) have been reported in the literature (Brand and Kollmeier, 2002).

The Speech Reception Threshold is typically determined using an adaptive procedure that employs lists containing a certain number of sentences: Each list corresponds to one acoustical test condition. For each sentence of a given list, the speech reproduction level is chosen as a function of the number of keyword identification errors made on the previous sentence, targeting 50% intelligibility. The SRT is defined as the SNR at the 50% intelligibility threshold, i.e. the speech level vs. the level of the distracting signal(s).

Speech material for SRT tests has to be similarly intelligible across sentences, and across lists. In terms of phonetic, syntactic and semantic complexity, the different lists, and the sentences composing the lists should thus be comparable. Such sentence material has been developed for several languages, like English, Dutch, German and Finnish (Rothauser et al., 1969; Plomp and Mimpfen, 1979; Wagener and Kollmeier, 2004; Vainio et al., 2005). In spite of numerous studies of speech quality in French, a French method for SRT measurement has not been developed to date. The available phonemically balanced French sentence material lacks the desired comparable complexity across sentences and lists, and thus cannot be used for the type of tests we aimed at (Combescure, 1981).

2. Test Development
Our goal was to assess the intelligibility linked to different configurations of a multi-user virtual speech-chat environment. Consequently, a method was needed enabling a large number of different conditions to be assessed in one test. This requirement is bound to a rather large number of different sentence lists, in order to minimize a potential training effect that ultimately could enhance intelligibility over the time. Moreover, we wanted our method to easily be portable to other languages. The test methods developed for other languages fulfil at least some of these criteria. Sentence material limited in the size of the underlying lexicon may lead to a comparable complexity over lists and may more easily be translated into other languages, but is typically accompanied by a measurable training effect (Wagener and Kollmeier, 2004). In turn, sentences that better reflect the actual usage of the language — e.g. by employing a far larger lexicon and more conversation-typical topics — reduce training effects, but are not easily portable to other languages.

2.1. SUS Database
As a compromise between training effect and homogeneous sentence complexity, we based our test method on the framework of semantically unpredictable sentences (Benoit et al., 1996). The underlying syntactic structures are very similar and thus of comparable complexity, and are available for different languages.

2.1.1. Text Material
Typically, the error-rate underlying an adaptive SRT-test is determined based on wrongly identified keywords. In order to achieve four keywords per sentence, only four of
The characteristics of the resulting French sentence material can be summarized as follows:

- **Word Lexicon** of the most frequent monosyllabic words based on word frequencies tabulated in database BRULEX, and with optimized phoneme distribution as compared to a reference distribution calculated from the databases BRULEX and LEXIQUE.

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1 Graphon is a grapheme-to-phoneme conversion engine showing less than 1% word error rate (Boula de Mareuil, 1997; Yvon et al., 1998).
Table 2: Information contained in word database underling the SUS text material. Resources: Morphalou (Romary et al., 2004; Salmon-Alt et al., 2004), BRULEX (Content et al., 1990), and LEXIQUE (New et al., 2004). Graphon is a grapheme-to-phoneme conversion engine showing less than 1% word error rate (Boula de Maretül, 1997; Yvon et al., 1998).

- Three repetitions of each word from the underlying lexicon.
- 24 lists of 12 sentences, leading to a total of 288 sentences. Each list contains 48 keywords.
- Minimized re-occurrence of word-pairs in another list.
- Chi-square-based maximization of the agreement between the phoneme-distribution of each list and the phoneme-distribution characteristic of the French language.
- Equalization of the word-frequencies per lexical category and per list.

Examples of the sentences are provided in Table 1.

2.1.2. Speech Material

The resulting sentences were recorded with a professional speaker of medium voice timbre. The speaker was instructed to read the sentences clearly but with a natural intonation reflecting the syntactic structures in an effort to avoid the rather artificial reading style often used by untrained readers of SUS-sentences, which reflects the lack of semantic predictability (Raake, 2002). The recordings were made with high-quality audio hardware in a soundproof acoustically treated environment. The samples were directly recorded to hard-disk at 48 kHz, 16 bits. After recording, the sentences were adjusted to an equal RMS (root mean square) level of -22 dB rel. overload of the digital system.

As reference distracter, a 60 s long speech-shaped stationary noise sample was created by twenty times overlaying and scaling of the original 288 sentences, with randomly selected, faded start and end instances. The resulting noise sample shows the same long-term spectrum as the underlying speech. The reference distracter was scaled to the same RMS as the target sentences.

3. Test System

The SRT-test presented in this paper is fully automatic. The sentences are entered by the subjects on the test PC.
The actual SRT-test is conducted as follows:

- The distracter signal is always played out at a fixed level throughout one list. The distracter signal is picked randomly from the distracter sound file, which was much longer than the target sentences. In addition, trailing periods of 500 ms were added in the beginning and the end of the target sentence to determine the necessary distracter duration.

- For the first of the twelve sentences of each list, the subject can repeatedly listen to the combined target and distracter samples. At each repetition, the target level is increased by 3 dB (starting at -25 dB signal-to-distracter-ratio). The subject switches to the next sentence, when she/he has the impression of understanding at least 50% of the sentence. The corresponding target level is stored and used as the starting play-out level for the following adaptive procedure, i.e. as the level of sentence #2/12. Since it only serves as the starting point of the procedure, the possible inaccuracy of this subject-decision is of minor importance for the remaining test.

- For sentences \(i \in [3, 12]\) the level is determined based on the number of wrongly detected keywords according to Equations (1)-(3) (Brand and Kollmeier, 2002):

\[
L_k = L_{k-1} + \Delta L_k \\
\Delta L_k = -\frac{f(i) \cdot (prev - 0.5)}{slope} \\
f(i) = 1.5 \cdot 1.41^{-1}
\]

Here, \(L_k\) is the level for the current target sentence. \(\Delta L_k\) is the level difference to the previous target sentence. For its derivation, the ratio of correctly identified keywords from the previous sentence is used \((prev)\), and an estimated slope of the psychometric function of intelligibility over signal-to-distracter-ratio of \(slope = 0.15\), as it was proposed by (Brand and Kollmeier, 2002). The function \(f(i)\) steers the convergence of the method: The higher the number of level-inversions \(i\), the lower \(f(i)\), and thus the lower the amount of level-change. For the reference distracter, i.e. the speech-shaped stationary noise, the slope of approximately 15%/dB was verified based on the calibration tests described in Section 4. Since this slope reflects a good compromise for different tests described in the literature (Brand and Kollmeier, 2002), it was used throughout our tests.

- The SRT is determined as the average level difference between target and distracter over the last 8 sentences (#5-12).

### 4. Test Calibration

In a two-step optimization procedure, the speech material was adjusted to homogeneous speech intelligibility in speech-shaped noise:

1. The average SRT was determined in an adaptive SRT intelligibility test for a sample of six of the 24 lists.
2. The estimated SRT was used as the SNR for all list/noise combinations, and all sentences were presented to a number of six subjects in a simple intelligibility test. From the word-errors determined in the
From the intelligibility-score/target level combinations collected in the test, a slope of approximately 15%/dB could be observed. Moreover, the SRT test results indicate both a strong subject-dependence, and a list index effect. In turn, with an initial training phase using two unscored runs with one training list each, no training effect was observed. In Figure 2, the SRT results for this first calibration test are plotted averaged over the test subjects. The left picture shows the results in the order of presentation, i.e. averaged over different lists. As can be seen from this picture and is further verified in the actual SRT tests, no significant training effect appears. The right graph depicts the results in the order of the underlying list indices. Here, each entry is averaged over the same list, showing the previously mentioned list effect.

In order to further investigate the source of the list-effect (i.e. that the measured SRT decreases with increasing list index or recording duration), the average speech activity and sentence-sample duration were determined for each list. Therefore, a simple voice activity detection was employed, which is based on a fixed level threshold. The trailing pauses at the beginning and end of each sentence-sample were excluded from the analysis, since these depend on the sample preparation rather than on the sentences themselves. Then, the speech activity of each sentence file was derived as the ratio of samples above the predefined level threshold vs. the overall number of samples. The second measure used for analyses simply was the overall number of samples. The results of these recording analyses are illustrated in Figure 3. As is depicted in the two graphs, speech activity and sample length change over recording duration (i.e. list index). Obviously, the reading style of the speaker slightly changed over time, with increasing pauses and thus increasing sentence durations. This observation is in line with the observed decrease of the SRT with increasing list index, since intelligibility is facilitated by the increasingly slower reading style.

4.1. First SRT estimate

The first calibration test was run with 12 subjects. Six of the 24 lists were presented to the subjects employing a digram-balanced test design according to (Wagenaar, 1969), with n=12. As distracter, the speech-shaped stationary noise was employed in all cases. As in all other tests, the sound samples were presented via Headphones (Sennheiser HD 600). In this test, an average SRT of -4.37 dB was obtained. From the intelligibility-score/target level combinations collected in the test, a slope of approximately 15%/dB could be observed. Moreover, the SRT test results indicate both a strong subject-dependence, and a list index effect. In turn, with an initial training phase using two unscored runs with one training list each, no training effect was observed. In Figure 2, the SRT results for this first calibration test are plotted averaged over the test subjects. The left picture shows the results in the order of presentation, i.e. averaged over different lists. As can be seen from this picture and is further verified in the actual SRT tests, no significant training effect appears. The right graph depicts the results in the order of the underlying list indices. Here, each entry is averaged over the same list, showing the previously mentioned list effect.

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4.2. Level Calibration

The second calibration test was conducted in order to reduce the SRT-differences between lists observed in the first calibration phase. Therefore, the target level was fixed to the SRT measured in the first test, i.e. $SRT = -4.37$. With this setting, a classical speech intelligibility test against the stationary speech-noise was run. Here, we assumed that the keyword intelligibility lies around the threshold of 50%. From the intelligibility scores obtained from the six subjects who participated in this second test, an error-rate-dependent level-correction was determined for each sentence, similarly to (Plomp and Mimpen, 1979). Corrections were only employed when the average intelligibility score for a given sentence was below 35% or higher than 65%, according to Equation (4). The corrections were limited to at most ±2 dB.

$$\text{LevCor}(i) = \begin{cases} 
(0.35 - I(i))/0.15, & I(i) < 0.35; \\
(0.65 - I(i))/0.15, & I(i) > 0.65. 
\end{cases}$$

(4)

5. Test Application

A number of SRT tests on speech intelligibility in multisource configurations in virtual auditory listening spaces have been carried out with the described method. All in all, three test series with 16 test conditions each were conducted, with 10 normal hearing subjects per test series. For clarity and brevity, we here will restrict ourselves to the reference condition with the speech-shaped stationary noise distracter and without e.g. spatial processing. The reference was used as the first test condition in all three tests.
The average SRT for this condition over the three tests is \( SRT = -4.7 \, dB \). Moreover, the results for this condition show a standard deviation below 1.2 dB for all three tests. Thus, the test method we have developed delivers accurate SRT-estimates in this case, which are comparable to or better than those obtained in other studies (Hawley et al., 2004; Vainio et al., 2005).

6. Conclusions

We have demonstrated a new method for measuring the speech reception threshold in French. It is based on a phonemically balanced keyword corpus used as the basis for automatically generated semantically unpredictable sentences. After pre-tests and calibration, the method delivers highly reliable estimates of the SRT in case of a stationary speech-shaped noise source (\( SRT = -4.6 \)). For our tests, we employed a new fully automatic procedure in order to reduce the considerable effort typically linked to adaptive SRT-tests. Due to the design of the method, error-sources like spelling errors by the subjects have been reduced to a far extent. Future work will address a detailed analysis of the effect of typographical errors on the accuracy of our automatic method. In addition, the method will be translated into other languages such as German and English, in order to investigate cross-language validity and reliability. The French method and SRT-corpus will further be used in our future studies of speech intelligibility in real and virtual environments. It is our aim to make the SUS text and speech corpora and, if desirable, the automated test available to interested parties. Please contact the authors for more information.

Acknowledgement

This work was conducted in the framework of the French Ministry of Research funded RNTL-project (Réseau National des Technologies Logicielles) OPERA (Optimisation PErecptive du Rendu Audio — Application au chat sonore 3D multi-utilisateurs et aux environnements virtuels réalisistes: http://www-sop.inria.fr/reves/OPERA). The authors wish to thank Patrick Paroubek, Philippe Boula de Mareüil and Marie-Neige Garcia for fruitful discussions and their support during the setting up of the SUS text database.

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