Better Evaluation of ASR in Speech Translation Context Using Word Embeddings

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Abstract
This paper investigates the evaluation of ASR in spoken language translation context. More precisely, we propose a simple extension of WER metric in order to penalize differently substitution errors according to their context using word embeddings. For instance, the proposed metric should catch near matches (mainly morphological variants) and penalize less this kind of error which has a more limited impact on translation performance. Our experiments show that the correlation of the new proposed metric with SLT performance is better than the one of WER. Oracle experiments are also conducted and show the ability of our metric to find better hypotheses (to be translated) in the ASR N-best. Finally, a preliminary experiment where ASR tuning is based on our new metric shows encouraging results. For reproducible experiments, the code allowing to call our modified WER and the corpora used are made available to the research community.

Index Terms: Spoken Language Translation, Automatic Speech Recognition, Evaluation Metrics, Correlations, Word Embeddings

1. Introduction
In spoken language translation (SLT), the ability of Word Error Rate (WER) metric to evaluate the real impact of the ASR module on the whole SLT pipeline is often questioned. This was investigated in past studies where researchers tried to propose a better evaluation of ASR in speech translation scenarios, [1] investigated how SLT performed as they changed speech decoder parameters. It was shown that sub-optimal WER values could give comparable BLEU scores at faster decoding speeds. The authors of [2] analyzed ASR error segments that have a high negative impact on SLT performance and demonstrated that removing such segments prior to translation can improve SLT. The same year, [3] proposed a Phonetically-Oriented Word Error Rate (POWER) for speech recognition evaluation which incorporates the alignment of phonemes to better trace the impact of Levenshtein error types in speech recognition on downstream tasks (such as information retrieval, spoken language understanding, speech translation, etc.). Moreover, the need to evaluate ASR speech recognition when its output is used by human subjects (predict how useful that ASR output would be to humans) was also highlighted by [4]. Finally, some authors [5] proposed an end-to-end BLEU-oriented global optimization of ASR system parameters in order to improve translation quality. However, such an end-to-end optimization is not always possible in practical applications where a same ASR system is designed for several downstream uses. Thus, we believe that a better evaluation of the ASR module itself should be investigated.

Contribution This paper rests upon the above papers as well as on the former research of [6] who noticed that many ASR substitution errors (the most frequent type of ASR error) are due to slight morphological changes (such as plural/singular substitution), limiting the impact on SLT performance. Thus, the current WER metric – which gives the same weight to any substitution – is probably sub-optimal for evaluating ASR module in a SLT framework. We propose a simple extension of WER in order to penalize differently substitution errors according to their context using word embeddings. For instance, the proposed metric should penalize less morphological changes that have a smaller impact on SLT. We specifically extend our existing French-English corpus for SLT evaluation and shows that the new proposed metric is better correlated with SLT performance. Oracle experiments are also conducted to show the ability of our metric to find better hypotheses (to be translated) in the ASR N-best. Finally, we propose a preliminary experiment where ASR tuning is based on our new metric. For reproducible experiments, the code allowing to call our modified WER and corpora used are made available to the research community.

Outline The rest of the paper goes simply as follows: section 2 summarizes related works on evaluation metrics that use word embeddings. Section 3 presents our modified WER metric which allows to consider near matches in substitution errors. Section 4 details the experimental settings and section 5 presents our results. Section 6 concludes this work.

2. Related works on evaluation metrics using word embeddings
Word embeddings are a representation of words in a continuous space. Mikolov and al. [7] have shown that these vector representations could be useful to detect near matches (like syntactic variants or synonyms). For this work, we decided to choose the representation proposed by [8] and implemented in the toolkit MultiVec [9]. The use of word embeddings has grown since the work done by Mikolov [8], especially in Natural Language Processing (NLP). Tasks such as machine translation [10], information retrieval [11] and many others, use continuous word representations. As far as we know, only few works used word embeddings for evaluation in NLP. One of them is the paper recently published by [12] which extends ROUGE, a metric used in text summarization. Concerning Machine Translation, [13] proposed a metric (for WMT 2015 metrics shared task) that represents both reference and translation hypotheses using a dependency Tree-LSTM and predicts the similarity score based on a neural network. In the same workshop, [14] used document embeddings for predicting MT adequacy. These two latter works are close to what we propose. However, they both rely on the training of the metric itself which questions its portability to evaluation on other domains / tasks. In our work, we propose to use word embeddings that are trained once and for all on a general corpus.
3. WER with embeddings (WER-E)

The Word Error Rate is the main metric applied to Automatic Speech Recognition evaluation. Its estimation is based on the Levenshtein distance, which is defined as the minimum number of editing steps needed to match an hypothesis and a reference.

\[
D_c(W_1, W_2) = 1 - S_c(W_1, W_2)
\]

From this, two variants of the metric are possible. Firstly, in table 2, we apply the WER alignment algorithm with classical substitution cost (we do not modify the alignment path of table 1) and we replace only the substitution scores by the cosine distance. We call it “WER with embeddings” (WER-E). Secondly, in table 3, we propose to replace substitution cost by the cosine distance to compute the best alignment path. We call this last WER variant “WER soft” (WER-S).

In the first case (table 2), we can observe a WER-E score (54%) lower than the classical WER estimation (78%). Since we do not question the alignment path in this case, we do not obtain the lowest score possible. The second case, presented in table 3, enables us to get another alignment path, and thus gets the lowest score possible (53%).

This new feature takes into account near matches between words. For instance, words “westphalie” and “westphalien” are close enough to have a low distance. In the alignment proposed in table 3, the alignment changed and we got a lower score.

3.1. Running exemple

In table 1, we compare an hypothesis (on the top) and a reference (on the left): the score is defined as the lowest-cost alignment path (in grey) from the beginning of both sentences (top left corner) to the end of both sentences (on the lower-right corner). The intensity of the colour in the alignment path indicates the match level: lighter grey for matches, dark-grey for substitutions and dark grey for insertions and deletions. The score sums the number of insertions, deletions and substitutions. Then, this sum is normalized by the length of the reference. In our example, the WER is 78% (0.78).

3.2. Adding word embeddings

The main drawback of WER is that it does not gives credit to near matches. For instance, in table 1, the hypothesis contains the word “souveraine”, which is close to the word “souveraines” in the reference. Both are morphological variants of a same word and WER considers this difference as a Substitution, while their cosine distance in the continuous space is only 0.43.

\[
\text{Cost: } 0 \quad 1.01 \quad 0.73 \quad 1 \quad 0 \quad 0.47 \quad 0 \quad 0.35 \quad 0.78 \quad 0.43
\]

Table 3: WER-S estimation with word embeddings. Substitution score is replaced by a cosine distance and we recalculate the best alignment.

4. Dataset and ASR, MT, SLT systems

For the experiments of this paper, we have extended our corpus presented in [16]. This corpus, available on a github repository\(^1\) contained initially 2643 French speech utterances (news domain) \(x_f\) for which a quintuplet containing: ASR output \(f_{hyp}\), verbatim transcript \(f_{ref}\), English text translation output \(e_{hyp}^{(en)}\), speech translation output \(e_{hyp}^{(fr)}\), and post-edition of translation \(e_{ref}^{(fr)}\), was made available. We recently added 4050 new sentences of the same (news) domain in our corpus (our github repository has been updated with this new data).

The initially available corpus (2643 utterances) will be referred to as dev set in the rest of the paper while the recently recorded part (4050 utterances) will be referred to as test set in the rest of the paper. For ASR output, the N-best lists (N=1000) were also generated for each utterance.

4.1. ASR system

To obtain the speech transcripts \(f_{hyp}\), we built a French ASR system based on KALDL toolkit [17]. It is trained using several corpora (ESTER, REPERE, ETAPA and BREF 120) representing more than 600 hours of transcribed speech. CD-DNN-HMM acoustic models are trained (43 182 context-dependent

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\(^1\)https://github.com/besacier/WCE-SLT-LIG/
states) and the 3-gram language model is learned on French ESTER corpus [18] as well as on French Gigaword (vocabulary size is 55k). The ASR system’s LM weight parameter is tuned through WER on the dev corpus. The output of our ASR system, scored against the ref reference is 21.92% WER on dev set and 17.46% WER on test set. This WER may appear as rather high according to the task (transcribing read news). A deeper analysis shows that these news contained a lot of foreign named entities, especially in our dev set. This part of the data is extracted from French medias dealing with European economy in EU. This could also explain why the scores are significantly different between dev and test sets. In addition, automatic post-processing is applied to ASR output in order to match requirements of standard input for machine translation.

4.2. SMT system

We used Moses phrase-based translation toolkit [19] to translate French ASR into English (en-fr). This medium-sized system was trained using a subset of data provided for IWSLT 2012 evaluation [20]: Europarl, Ted and News-Commentary corpora. The total amount is about 60M words. We used an adapted target language model trained on specific data (News Crawlled corpora) similar to our evaluation corpus (see [21]). Table 4 gives 2 examples of SLT output obtained. Table 5 summarizes baseline ASR, MT and SLT performances obtained on our corpora. We score translations obtained with the following automatic metrics: TER [22], BLEU [23] and METEOR [24] using post-edition references (e_ref).

5. Experiments and results

This section first presents the results obtained in ASR, according to our new metrics. Then, we analyze the correlation of the ASR metrics (WER, WER-E, WER-S) with SLT performances. After that, Oracle experiments are conducted to compare the ASR metrics in their ability to find (before translation) promising hypotheses in the ASR N-best. Finally, a preliminary experiment where ASR tuning is based on our new metric is proposed. For all the experiments, the MT system never changes and is the one described in section 4.

5.1. ASR results

Table 6 presents the performances obtained by the ASR system described in section 4. The columns correspond to four settings: the best output according to the ASR system, and three oracles extracted from the N-best list. The oracle ASR performances are obtained by sorting the N-best hypotheses according to WER, WER-E or WER-S. The results show that the oracle hypotheses selected by WER, WER-E and WER-S can be different. In other words, optimizing the ASR according to the new metrics proposed can degrade WER but improve WER-E or WER-S. In this case, better ASR outputs in terms of near matches are selected. Overall, whatever the metric used, Oracle hypotheses contain approximately 50% of the initial errors found in the 1-best.

5.2. Correlation between ASR metrics and SLT performance

In this section, we investigate if our new metrics WER-E and WER-S are better correlated with speech translation (SLT) performance. Table 7 shows the correlation (Pearson) between ASR metrics (WER, WER-E or WER-S) and SLT performances (TER, BLEU, METEOR). Since BLEU and METEOR are not very efficient to evaluate translations at the sentence level, we

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### Table 4: ASR and SLT examples (explanations given in section 5.5)

<table>
<thead>
<tr>
<th>Tasks</th>
<th>metrics</th>
<th>ASR Ref</th>
<th>ASR 1-best</th>
</tr>
</thead>
<tbody>
<tr>
<td>dev</td>
<td>WER</td>
<td>38.84</td>
<td>21.92</td>
</tr>
<tr>
<td></td>
<td>TER</td>
<td>43.05</td>
<td>30.81</td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>40.73</td>
<td>34.02</td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>45.64</td>
<td>58.70</td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>44.71</td>
<td>34.27</td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>39.10</td>
<td>34.27</td>
</tr>
<tr>
<td>test</td>
<td>WER</td>
<td>-</td>
<td>17.46</td>
</tr>
<tr>
<td></td>
<td>TER</td>
<td>46.54</td>
<td>58.70</td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>44.71</td>
<td>34.27</td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>39.10</td>
<td>34.27</td>
</tr>
</tbody>
</table>

Table 5: Baseline ASR, MT and SLT performance on our dev and test sets - translations are scored w/o punctuation

<table>
<thead>
<tr>
<th>Tasks</th>
<th>metrics</th>
<th>ASR Ref</th>
<th>ASR 1-best</th>
</tr>
</thead>
<tbody>
<tr>
<td>dev</td>
<td>WER</td>
<td>-</td>
<td>21.92</td>
</tr>
<tr>
<td></td>
<td>WER-E</td>
<td>38.84</td>
<td>21.92</td>
</tr>
<tr>
<td></td>
<td>WER-S</td>
<td>43.05</td>
<td>30.81</td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>40.73</td>
<td>34.02</td>
</tr>
<tr>
<td></td>
<td>WER</td>
<td>-</td>
<td>17.46</td>
</tr>
<tr>
<td></td>
<td>TER</td>
<td>45.64</td>
<td>58.70</td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>44.71</td>
<td>34.27</td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>39.10</td>
<td>34.27</td>
</tr>
</tbody>
</table>

Table 6: Speech Recognition (ASR) performance – ASR Oracle is obtained from 1000-best list by selecting hypothesis that minimizes WER, WER-E or WER-S

<table>
<thead>
<tr>
<th>Tasks</th>
<th>metrics</th>
<th>ASR 1-best</th>
<th>Oracle from N-best</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WER</td>
<td>12.01</td>
<td>12.15</td>
</tr>
<tr>
<td></td>
<td>WER-E</td>
<td>18.10</td>
<td>10.45</td>
</tr>
<tr>
<td></td>
<td>WER-S</td>
<td>17.41</td>
<td>9.79</td>
</tr>
<tr>
<td></td>
<td>WER</td>
<td>17.46</td>
<td>7.38</td>
</tr>
<tr>
<td></td>
<td>WER-E</td>
<td>13.13</td>
<td>5.86</td>
</tr>
<tr>
<td></td>
<td>WER-S</td>
<td>12.53</td>
<td>5.65</td>
</tr>
</tbody>
</table>

Table 7: Pearson Correlation between ASR metrics (WER, WER-E or WER-S) and SLT performances (TER, BLEU, METEOR) - each point measured on blocks of 100 sentences
5.3. Oracle analysis
In this section, we verify if the hypotheses selected by WER-E and WER-S are more promising for translation. Our Oracle analysis is presented in Table 8. Similarly to Table 6, the columns correspond to four settings: the best output according to the ASR system is translated, and three oracles are scored by translating the most promising hypotheses according to WER, WER-E or WER-S. Even if there are not big differences in SLT performance, the results show the ability of our metric to find slightly better hypotheses (to be translated) in the ASR N-best. For instance, when the WER-S score is used to select the best ASR hypothesis, the TER, BLEU and METEOR are improved by respectively 0.18, 0.12, and 0.06 points on the dev corpus.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>metrics</th>
<th>ASR 1-best</th>
<th>Oracle from N-best</th>
<th>WER</th>
<th>WER-E</th>
<th>WER-S</th>
</tr>
</thead>
<tbody>
<tr>
<td>dev</td>
<td>TER</td>
<td>55.64</td>
<td>50.62</td>
<td>50.52</td>
<td><strong>50.45</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>30.81</td>
<td>35.29</td>
<td>35.37</td>
<td><strong>35.41</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>34.02</td>
<td>36.37</td>
<td>36.42</td>
<td><strong>36.44</strong></td>
<td></td>
</tr>
<tr>
<td>test</td>
<td>TER</td>
<td>58.70</td>
<td>54.13</td>
<td>54.01</td>
<td>54.03</td>
<td></td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>34.27</td>
<td>39.34</td>
<td>39.43</td>
<td>39.42</td>
<td></td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>34.27</td>
<td>36.55</td>
<td>36.64</td>
<td><strong>36.64</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 8: Speech Translation (SLT) performances - Oracle is obtained from 1000-best list by translating hypothesis that minimizes WER, WER-E or WER-S.

Table 9 shows this comparison for the three MT metrics (TER, sentenceBLEU and METEOR). Even if we logically observe a majority of ties where Oracle (according to WER-E) and Oracle (according to WER) lead to the same SLT output, for the other cases the analysis shows a preference of the translation metrics for the Oracle (according to WER-E). This result confirms the trend observed in table 8.

5.5. Translation examples
In this section, we verify if the hypotheses selected by WER-E and WER-S are more promising for translation. Our Oracle analysis is presented in Table 8. Similarly to Table 6, the columns correspond to four settings: the best output according to the ASR system is translated, and three oracles are scored by translating the most promising hypotheses according to WER, WER-E or WER-S. Even if there are not big differences in SLT performance, the results show the ability of our metric to find slightly better hypotheses (to be translated) in the ASR N-best. For instance, when the WER-S score is used to select the best ASR hypothesis, the TER, BLEU and METEOR are improved by respectively 0.18, 0.12, and 0.06 points on the dev corpus.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>Comparison</th>
<th>TER</th>
<th>BLEU</th>
<th>METEOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dev</td>
<td>O. WER-E best</td>
<td>255</td>
<td>310</td>
<td>321</td>
</tr>
<tr>
<td></td>
<td>O. WER best</td>
<td>190</td>
<td>271</td>
<td>315</td>
</tr>
<tr>
<td></td>
<td>Ties</td>
<td>2198</td>
<td>2062</td>
<td>2007</td>
</tr>
<tr>
<td>Test</td>
<td>O. WER-E best</td>
<td>341</td>
<td>451</td>
<td>510</td>
</tr>
<tr>
<td></td>
<td>O. WER best</td>
<td>264</td>
<td>381</td>
<td>399</td>
</tr>
<tr>
<td></td>
<td>Ties</td>
<td>3445</td>
<td>3218</td>
<td>3141</td>
</tr>
</tbody>
</table>

Table 9: Comparison of SLT performances of the Oracle WER vs. the Oracle WER-E by counting the number of sentences which obtain a better MT score according to TER, Sentence BLEU and METEOR.

5.4. ASR optimization for SLT
This section investigates if the tuning of an ASR system using the new metrics proposed can lead to real (and not oracle) improvements. This experiment is preliminary since we only optimize the LM weight parameter (to minimize WER or WER-E) on the dev corpus.

The results are given in Table 10 but they are not very convincing: we observe small gains for TER and BLEU evaluation but not improvement of METEOR. Our explanation is that there were too few free parameters investigated to tune the ASR system. In addition, translation evaluation metrics are themselves unperfect to evaluate translation quality. The next section proposes to analyze a few translation examples to better understand the differences of both SLT systems.

<table>
<thead>
<tr>
<th>Tasks</th>
<th>metrics</th>
<th>ASR optimized with WER</th>
<th>ASR optimized with WER-E</th>
</tr>
</thead>
<tbody>
<tr>
<td>dev</td>
<td>TER</td>
<td>55.64</td>
<td>55.52</td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>30.81</td>
<td><strong>30.84</strong></td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>34.02</td>
<td>34.00</td>
</tr>
<tr>
<td>test</td>
<td>TER</td>
<td>58.71</td>
<td><strong>58.56</strong></td>
</tr>
<tr>
<td></td>
<td>BLEU</td>
<td>34.27</td>
<td><strong>34.38</strong></td>
</tr>
<tr>
<td></td>
<td>METEOR</td>
<td>34.27</td>
<td>34.26</td>
</tr>
</tbody>
</table>

Table 10: Speech Translation (SLT) scores obtained with 2 ASR systems optimized with WER or WER-E.

6. Conclusions
We proposed an extension of WER in order to penalize differently substitution errors according to their context using word embeddings. Our experiments, made on a French-English speech translation task, have shown that the new proposed metric is better correlated with SLT performance. Oracle experiments have also shown a trend: the ability of our metric to find better hypotheses (to be translated) in the ASR N-best. This opens possibilities to optimize ASR using metrics clever than WER. For reproducible experiments, code allowing to call our modified WER is made available on github.

7. Acknowledgements
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8. References
[1] P. R. Dixon, A. Finch, C. Hori, and H. Kashioka, “Investigation on the effects of ASR tuning on speech trans-
lation performance,” in The proceedings of the Interna-
tional Workshop on Spoken Language Translation (IWSLT
2011), San Francisco, CA, USA, December 2011.

[2] F. Bechet, B. Favre, and M. Rouvier, “speech is silver,
but silence is golden”: improving speech-to-speech trans-
lation performance by slashing users input,” in Proceed-
ings of Interspeech 2015, Dresden, Germany, September 2015.

error alignment for speech recognition error analysis in
speech translation,” in IEEE 2015 Workshop on Automatic
Speech Recognition and Understanding, December 2015.

C. Munteanu, A. Nenkova, D. Ochei, G. Penn, S. Tratz,
C. Voss, and F. Zeller, “Automatic Human Utility Eval-
uation of ASR Systems: Does WER Really Predict Per-
formance?” in Proceedings of Interspeech 2013, Lyon,
France, August 2013.

[5] X. He, L. Deng, and A. Acero, “Why word error rate is
not a good metric for speech recognizer training for the
speech translation task?” in Acoustics, Speech and Signal
Processing (ICASSP), 2011 IEEE International Confer-
ence on, May 2011.

of statistical machine translation output,” in Proceedings of

ities in continuous space word representations;” in Proceed-
ings of the 2013 Conference of the North American
Chapter of the Association for Computational Linguistics:
Human Language Technologies, Atlanta, GA, USA, June
2013.

estimation of word representations in vector space;” in The
Workshop Proceedings of the International Conference on
Learning Representations (ICLR) 2013, Scottsdale, AR,
USA, May 2013.

“MultiVec: a Multilingual and Multilevel Representation
Learning Toolkit for NLP,” in The 10th edition of the
Language Resources and Evaluation Conference (LREC
2016), May 2016.

[10] K. Cho, B. van Merrienboer, C. Gulcehre, D. Bahdanau,
F. Bougares, H. Schwenk, and Y. Bengio, “Learning
phrase representations using rnn encoder–decoder for sta-
tistical machine translation;” in Proceedings of the 2014
Conference on Empirical Methods in Natural Language
Processing (EMNLP), Doha, Qatar, October 2014.

semantic model with convolutional-pooling structure for
information retrieval;” in Proceedings of the 23rd ACM
International Conference on Conference on Information
and Knowledge Management, November 2014.

with word embeddings for ROUGE,” in In The Proceed-
ings of the Conference on Empirical Methods in Natural
Language Processing (EMNLP), Lisbon, Portugal,
September 2015.

lation evaluation using recurrent neural networks;” in Pro-
ceddings Workshop on Machine Translation (WMT), Met-
rics Shared Task, Lisbon, Portugal, September 2015.

[14] M. Vela and L. Tan, “Predicting machine translation ade-
quacy with document embeddings,” in Proceedings Work-
shop on Machine Translation (WMT), Metrics Shared
Task, Lisbon, Portugal, 2015.

[15] T. Mikolov, J. Sutskever, K. Chen, G. S. Corrado, and
J. Dean, “Distributed representations of words and phrases
and their compositionality;” in Advances in Neural In-
f ormation Processing Systems 26, C. Burges, L. Bottou,

[16] L. Besacier, B. Lecouteux, N. Q. Luong, K. Hour, and
M. Hadjelsah, “Word confidence estimation for speech
translation,” in Proceedings of The International Work-
shop on Spoken Language Translation (IWSLT), Lake
Tahoe, CA, USA, December 2014.

[17] D. Povey, A. Ghoshal, G. Boulianne, L. Burget, O. Glem-
bek, N. Goel, M. Hannemann, P. Motlicek, Y. Qian,
P. Schwarz, J. Silovsky, G. Stemmer, and K. Vesely, “The
calidi speech recognition toolkit,” in IEEE 2011 Work-
shop on Automatic Speech Recognition and Under-
standing, December 2011.

D. Mostefa, and K. Choukri, “Corpus description of the
aster evaluation campaign for the rich transcription of
french broadcast news,” in In Proceedings of the 5th in-
ternational Conference on Language Resources and Eval-
uation (LREC 2006), 2006.

erico, N. Bertoldi, B. Cowan, W. Shen, C. Moran, R. Zens,
C. Dyer, O. Bojar, A. Constantin, and E. Herbst, “Moses:
Open Source Toolkit for Statistical Machine Translation,”
in Proceedings of the 45th Annual Meeting of the Asso-
ciation for Computational Linguistics, Prague, Czech

S. Stüker, “Overview of the IWSLT 2012 Evaluation Campa-
in,” in Proceedings of the 9th InternationalWork-
shop on Spoken Language Translation (IWSLT), Decem-
ber 2012.

[21] M. Potet, L. Besacier, and H. Blanchon, “The LIG ma-
chine translation system for WMT 2010,” in Proceedings
of the joint fifth Workshop on Statistical Machine Transla-
tion and Metrics MATR (WMT2010), A. Workshop, Ed.,
Uppsala, Sweden, July 2010.

[22] M. Snover, B. Dorr, R. Schwartz, L. Miccio, and
J. Makhoul, “A study of translation edit rate with targeted
human annotation,” in Proceedings of association for ma-

method for automatic evaluation of machine translation,” in
ACL, 2002.

ic for MT Evaluation with Improved Correlation with
Human Judgments,” in Workshop on Intrinsic and Extrinsic
Evaluation Measures for MT and/or Summarization at the
43th Annual Meeting of the Association of Compu-
tational Linguistics, 2005.