Study of Electronic Pen Commands for Interactive-Predictive Machine Translation

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Typically, the post-editing of a machine translation (MT) output consists in performing a series of editing operations (ie., replace, delete, insert or move pieces of text) in a specific text editor using the keyboard and occasionally the mouse. This approach has been proved to be efficient by the translation industry to the point that [1] proposes post-editing guidelines for translation agencies. However, the user needs to be in front of a desktop computer which imposes some restrictions regarding where and how the work is to be done. Laptop computers can also be used, although arguably performance could be diminished because of the use of uncomfortable laptop keyboards and track pads.

In this work, we envision an alternative scenario in which the user can use a touch screen or an electronic pen (e-pen) to perform post-editing tasks. Although e-pen interaction may sound impractical for texts that need a large amount of post-editing, there is a number of circumstances where it can be more comfortable. First, it can be well suited for post-editing sentences with few errors, as it is the case of sentences with high fuzzy matches, or the revision of human post-edited sentences. Second, it would allow to perform such tasks while commuting, traveling or sitting comfortably on the couch in the living room.

There is already a 'de facto' standard for gestures for proof reading (cf. Figure 1) from which we have extracted the most promising gestures: substitutions, deletions, insertions and, transpositions. Furthermore, we have added a shift gesture to move phrases to specific places in the text (i.e., the user circles the phrase and draws an arrow to the final destination). Then, we have studied two e-pen post-editing approaches. In the first one, we consider substitutions, deletions, insertions and, shifts. The number of these operations to obtain a reference can be computed with the translation error rate (TER) [2]. In the second approach, we assume that the user is working with an interactive-predictive MT system (IMT) [3]. In IMT, the user and the MT system collaborate to produce a high-quality output. The user locates the first error from left-to-right and amends it. Then, leveraging the recently validated text, the system reformulates (predicts) the continuation of the translation aiming to improve the previous hypothesis. In this case, we have also considered transpositions.

To know what gestures could be more useful, we have conducted an experiment on the Xerox corpus [4]. The Xerox corpus consists of a collection of technical manuals. It consists of 56k sentences of training and a development and test sets of 1.1k sentences. Test perplexities for Spanish and English are 35 and 51, respectively. The summary of the edit rate results is displayed in Table 1. The edit rate is the number of edit operations needed to obtain the

Symbol	Meaning	Example
	insert a comma	The mayor's brother I tell you is a crook.
	apostrophe or single quotation mark	I wouldnt know where to put this vase.
	insert something	I know it in fact, everyone knows it.
	use double quotation marks	May favorite poem is Design.
	use a period here	This is a declarative sentence
	delete	The elephant's trunk is really its nose.
	transpose elements	He only picked the one he likes.
	close up this space	Jordan lost his favorite basket ball.
	a space needed here	I have only threefriends: Ted, Raoul, and Alice.
	begin new paragraph	"I know it," I said. "I thought so," she replied.
No	no paragraph	"I knew it, she said. No "He's no good."
	lowercase	Lunch was Delicious.
	capitalize	Tell me what i should do.

Figure 1: List of 'de facto' standard proof reading symbols obtained from `editorwriter.org`

reference normalized by the number of words. We can see that the IMT system requires less interactions, especially for es-en. Next, the number of times a particular edit operation has been applied is shown. We expect the gestures for deletion, insertion, shifting and transposition to be easy to tell apart for a machine learning algorithm. However, this will be the subject of future work. In addition, substitutions or insertions require the user to write the correct word, which can be done with a virtual keyboard or by handwriting [5]. The perplexities for these words is 336 for English and 242 for Spanish, whereas the errors rates for handwriting recognition are 7.4 for English and 8.9 for Spanish.

References

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	post-editing		IMT	
	en-es	es-en	en-es	es-en
edit rate (%)	21.3	24.4	21.1	22.8
substitutions	1028	919	1549	1284
insertions	325	461	190	212
deletions	484	302	0	0
transpositions	–	–	41	56
shifts	319	357	347	354

Table 1: Summary of number of edit operations needed to obtain the reference for post-editing and interactive-predictive machine translation. The edit rate is the ratio between the number of edit operations and the number of words in the reference. Follows the number of occurrences for each edit operation. Here, we assume a perfect gesture recognizer. The gesture recognizer will be developed in future work.

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