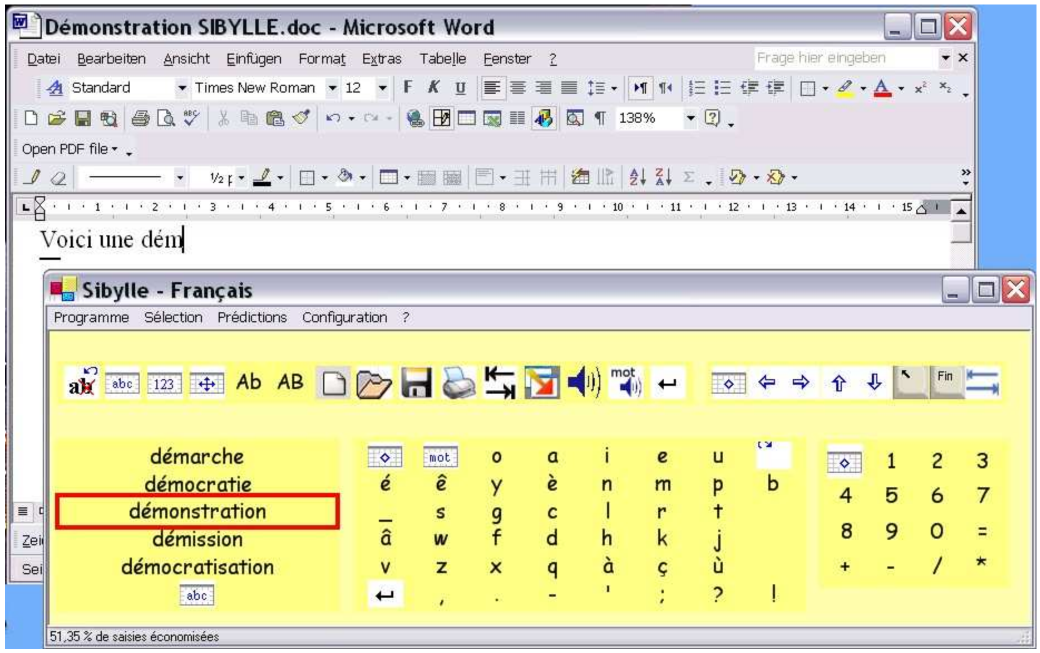

Figure 1: User interface of the *SIBYLLE* AAC system

Two complementary approaches are possible to speed up communication. The first one aims at minimizing the duration of each item selection. Considering a linear scan procedure, one could for instance dynamically reorganize the keyboard in order to present the most probable symbols at first. The second strategy tries to minimize the number of keystrokes to be made. Here, the system tries to predict the words which are likely to occur just after those already typed. The predicted word is then either directly displayed after the end of the inserted text (a method referred to as “word completion”, cf. Boissière and Dours, 1996), or a list of N-best (typically 3 to 7) predictions is provided on the virtual keyboard. When one of these predictions corresponds to the intended word, it can be selected by the user. As can be seen in figure 1, the interface of the *SIBYLLE* system presents such a list of most probable words to the user.

Several approaches can be used to carry out word prediction. Most of the commercial AAC systems make only use of a simple lexicon: in this approach, the context is not considered.

On the other hand, stochastic language models can provide a list of word suggestions, depending on the *n-1* (typically $n = 3$ or 4) last inserted words. It is obvious that such a model cannot take into account long-distance dependencies. There have been attempts to integrate part-of-speech information (Fazly and Hirst, 2003) or more complex syntactic models (Schadle et al, 2004) to achieve a better prediction. In this paper, we will nevertheless limit our study to a standard 4-gram model as a baseline to make our results comparable. Our main aim is here to investigate the use of long-distance semantic dependencies to dynamically adapt the prediction to the current semantic context of communication. Similar work has been done by Li and Hirst (2005) and Matiasek and Baroni (2003), who exploit *Pointwise Mutual Information* (PMI; Church and Hanks, 1989). Trnka et al. (2005) dynamically interpolate a high number of topic-oriented models in order to adapt their predictions to the current topic of the text or conversation.

Classically, word predictors are evaluated by an objective metric called *Keystroke Saving Rate* (*ksr*):

$$ksr_n = \left(1 - \frac{k_p}{k_a}\right) \cdot 100 \qquad (1)$$

with k_p, k_a being the number of keystrokes needed on the input device when typing a message with (k_p) and without prediction (k_a = number of characters in the text that has been entered, n = length of the prediction list, usually $n = 5$). As