A VIEW of Russian: Visual Input Enhancement and adaptive feedback

Robert Reynolds[1], *Eduard Schaf*[2], *Detmar Meurers*[1,2]

(1) University of Tromsø, Department of Language and Linguistics
(2) University of Tübingen, Department of Linguistics

robert.reynolds@uit.no, eduard.schaf@student.uni-tuebingen.de,
detmar.meurers@uni-tuebingen.de

ABSTRACT
We explore the challenges and opportunities which arise in developing automatic visual input enhancement activities for Russian with a focus on target selection and adaptive feedback. Russian, a language with a rich fusional morphology, has many syntactically relevant forms that are not transparent to the language learner, which makes it a good candidate for visual input enhancement (VIE). VIE essentially supports incidental focus on form by increasing the salience of language forms to support noticing by the learner. The freely available VIEW system (Meurers et al., 2010) was designed to automatically generate VIE activities from any web content. We extend VIEW to Russian and discuss connected research issues regarding target selection, ambiguity management, prompt generation, and distractor generation. We show that the same information and techniques used for target selection can often be repurposed for adaptive feedback. Authentic Text ICALL (ATICALL) systems incorporating only native-language NLP, without the NLP analysis specific to learner language that is characteristic of Intelligent Language Tutoring Systems (ILTS), thus can support some forms of adaptive feedback. ATICALL and ILTS represent a spectrum of possibilities rather than two categorically distinct enterprises.

KEYWORDS: CALL, ICALL, ATICALL, input enhancement, noticing, consciousness raising, adaptive feedback, scaffolding, part-of-speech tagging, finite-state technology, Constraint Grammar, Russian, stress, aspect, participles, case.

Robert Reynolds, Eduard Schaf and Detmar Meurers 2014. A VIEW of Russian: Visual Input Enhancement and adaptive feedback. *Proceedings of the third workshop on NLP for computer-assisted language learning.* NEALT Proceedings Series 22 / Linköping Electronic Conference Proceedings 107: 98–112.

1 Introduction

Intelligent Computer-Assisted Language Learning (ICALL) has been characterized (Meurers, 2012) as consisting of two distinct areas, Intelligent Language Tutoring Systems (ILTS) and Authentic Text ICALL (ATICALL). In the former, researchers have focused on the challenge of analyzing learner language and providing adaptive feedback. In the latter, research employs standard NLP tools developed for native language to identify and enhance authentic texts in the target language. While this seems like a categorical difference in some respects, in this article we want to show that it can be attractive to combine aspects of both approaches. We describe how an ATICALL system can incorporate a feature typical of ILTS: adaptive feedback to learner responses. The idea is explored using language activities for Russian, a language with a rich, fusional morphology that is challenging for second language learners. We showcase four of the Russian activities that we developed on top of the freely available VIEW platform (Meurers et al., 2010).

Russian Morphological Analysis Most Russian grammar books focus primarily on morphology, a serious challenge to most learners. Russian has a highly fusional morphology, with nominal inflection for six cases, two numbers, and three genders. There are three noun declension paradigms, each containing 12 forms. Adjectival modifiers have at least 24 forms. Russian verbs represent a relatively extensive inflectional system, similar to other Indo-European languages. A related difficulty is that Russian stress is phonemic, differentiating both lexical and inflectional homographs. This causes difficulties for learners, since there is a complex system of lexically specified stress placement, yet stress is almost never marked in the written language.

In order to build an ATICALL system for Russian, we need a fast, broad-coverage morphological engine to both analyze and generate word forms. In addition to the usual demands of a general-purpose morphological engine, we also need to generate stressed word forms. No open-source state-of-the art tools we are aware of provide this functionality. Thus a Russian Finite-State Transducer (FST) was developed (Reynolds, 2014) using the two-level formalism (Koskenniemi, 1983). The transducer was originally based on Zaliznjak (1977) ($\approx$ 120 000 words), which is the foundation for most Russian computational morphologies. Additional words, especially proper nouns, are continually being added. Since Russian has systematic syncretism and widespread homonymy, a constraint grammar (Karlsson et al., 1995) implemented in the freely available CG3 system[1] is used to disambiguate multiple readings.

Most state-of-the-art part of speech taggers for Russian are based on finite-state transducers, including *AOT/Dialing* (Nozhov, 2003), and *mystem* (Segalovich, 2003). Finite-state methods make it possible to provide efficient and robust computational analyses with wide empirical coverage, while keeping a clear conceptual distinction between the linguistic system and its usage. Finite-state methods also have several characteristics that make them especially well suited for ICALL. A finite-state analysis keeps track of what it knows, which allows an ATICALL system to focus only on targets that are clearly identifiable. Since finite-state tools provide an actual linguistic model of the language being analyzed, it is possible to identify and increase the salience of linguistic characteristics known to be relevant in language learning. A good case in point is stress placement, which is lexical, yet requires syntactic disambiguation. The finite state analysis provides effective access to subsets of data for certain grammar topics (e.g., retrieve all words with a particular stress pattern), since this information is modeled in the FST source files. Mistakes and errors in the system can be diagnosed and corrected.

[1] `http://beta.visl.sdu.dk/cg3.html`

This is especially important in ICALL, where low precision in the analysis leads to unreliable output easily confusing and frustrating learners. And, importantly in the context of ATICALL involving activities with distractors, a finite-state morphological analyzer can simply be reversed to become a generator.

Visual Input Enhancement Researchers in second language acquisition agree that comprehensible input is necessary for language learning. The Noticing Hypothesis (Schmidt, 1990) extends this claim to say that noticing of grammatical categories and relations also is required for successful second language acquisition. Based on the Noticing Hypothesis and related work on Consciousness Raising (Rutherford and Sharwood Smith, 1985) and Input Enhancement (Sharwood Smith, 1993, p. 176), researchers have investigated Visual Input Enhancement (VIE) to encourage learners to notice the grammatical forms in comprehensible input. VIE refers to the graphical enhancement of written text to draw attention to targeted grammatical structures. Various modes of enhancement have been suggested, such as font manipulation (e.g., bold, italic, color), capitalization, and other notations (e.g., underlining, circling). Such textual enhancements are intended to increase the likelihood that the learner will notice the target grammatical form in its grammatical and functional context of use.

Visual Input Enhancement of the Web (VIEW) is an ATICALL system designed to automatically generate learning activities from user-selected texts on the web. A description of the system architecture can be found in Meurers et al. (2010). VIEW includes four activity types to guide the learner from recognition via practice to production. The *highlight* activity adds color to target wordforms. The *click* activity allows the learner to identify target wordforms in the text. The *multiple-choice* activity provides controlled practice, allowing the learner to choose the correct form from a multiple-choice list. The *practice* activity asks learners to type the wordforms themselves. The activities can be accessed as a web application on a webpage or through a toolbar provided as a Firefox web browser Add-on. Activities have previously been developed for English, German, and Spanish. The open-source research prototype is available at `http://purl.org/icall/view`.

The following issues were considered in developing the activities for Russian:

1. Learner needs: What are the needs of the learner?
2. Feasibility: Can the target construction be reliably identified using NLP?
3. Target selection: Which tokens of the target construction should be focused?
4. Prompt generation: What kind of prompt can sufficiently constrain the learner productions for practice? (cf. Amaral and Meurers, 2011, sec. 3.1)
5. Generation of distractors for multiple-choice activities: What forms can or should serve as distractors? How does Second Language Acquisition (SLA) research help us with this, and how does the systematicity of the linguistic system allow us to generate distractors?
6. Feedback: What kind of feedback does the learner receive for (in)correct answers, under a perspective conceiving of feedback as *scaffolding* guiding the learner in their Zone of Proximal Development (Vygotsky, 1986)?

Related work Although research in Russian NLP for language learning has not been as extensive as for English and some other languages, some significant inroads have been made. One string of research is concerned with methods for identifying Russian texts at a suitable reading level for language learners. Sharoff et al. (2008) use a Principle Component Analysis to analyze the lexical and grammatical complexity of texts in a variety of languages, including

Russian. Similarly, Karpov et al. (2014) train a variety of machine-learning models on a small corpus of texts categorized by CEFR level, with promising results.

Another set of studies has been dedicated to Russian Intelligent Tutoring Systems. The Boltun project[2] has as one of its goals to develop NLP resources for ICALL, especially for analyzing learner language (Dickinson and Herring, 2008a,b; Dickinson, 2010). Another project, KLIOS, is a Learning Management System being developed specifically for Russian foreign language learning (Gorisev et al., 2013). KLIOS apparently makes use of the existing general-purpose tagger pymorphy2[3] and parser ABBYY Compreno[4], but not enough information is currently available to draw meaningful comparisons of the activities and analyses to our work on the Russian VIEW.

Goal and Structure of the Paper The goal of this article is to explore the ability of authentic text ICALL systems to provide adaptive feedback to learners. In doing so, we also demonstrate some features of the Russian VIEW system that we are currently developing, for which a prototype can be found at `http://purl.org/icall/rusVIEW`. In section 2, we introduce exercises for four separate target grammatical topics: Stress, Noun Declension, Aspect, and Participles. For each topic, we discuss the pedagogical motivation for the exercises, as well as relevant practical and theoretical issues that arose during development. Special attention is given to factors involved in target selection since these factors become relevant in the subsequent discussion. In section 3, we show how the same technology and strategies used in target selection can be used to provide adaptive feedback. Section 4 summarizes the contributions of the article and considers options for evaluating the approach.

2 Key topics for Russian learners

The following grammar topics are generally difficult for learners, relatively ubiquitous, and they allow us to exemplify central issues in visual input enhancement and the computational modeling it is built on. Section 2.1 introduces a basic example, highlighting the morphological analysis in a noun declension activity. The discussion of target selection for this activity illustrates the need to distinguish between grammatically and referentially determined morphosyntactic properties. Section 2.2 discusses activities for word stress, where target selection is primarily lexical, but is also concerned with managing the ambiguity that arises in rule-based morphologies. Section 2.3 outlines verbal aspect activities, where target selection is complicated by limitations in determining whether the learner should be able to deduce the aspect of each token. Section 2.4 presents participles activities, which demonstrate a more complicated use of wordform generation for providing prompts to guide learners' responses in multiple-choice and cloze activities.

2.1 Noun declension

The relatively extensive nominal inflection system is one of the first major hurdles for most Russian learners. Learners whose L1 does not have similar noun declension frequently seem to ignore inflectional endings. A visual input enhancement activity has the potential to boost learning by raising awareness of those endings.

We developed activities targeting specific case distinctions known to be difficult, but in this

[2] `http://cl.indiana.edu/~boltundevelopment`
[3] `https://pymorphy2.readthedocs.org`
[4] `http://www.abbyy.ru/isearch/compreno`

article we focus on describing the multiple-choice activity developed for all cases, since that activity makes it possible to illustrate both the underlying NLP and some points regarding target selection. When learners select this activity for a web page, VIEW replaces some nouns in the text with dropdown boxes containing the original noun in all of its case forms as options.

Target selection As a rule, each noun declension paradigm has 12 cells (six cases, singular and plural), but some forms are syncretic. For example, prototypical masculine nouns have ten unique forms, feminine and neuter nouns have nine, and the soft-consonant feminine nouns have only seven unique forms. Although our constraint grammar is able to disambiguate many syncretic forms, some ambiguity still remains in our analyses. One might expect that ambiguity in the analysis would complicate target selection, but this is only true if the analysis is ambiguous with regard to number. This is because a number ambiguity may be a referential ambiguity that cannot be resolved by checking contextual clues, as illustrated in (1).

(1) He saw the ______ (dancer/dancers).

Without additional context, such as a picture, this would be a confusing exercise given that both *dancer* and *dancers* are grammatically correct. Given this potential difficulty, we do not select tokens for which number is grammatically ambiguous.

Distractor generation After selecting targets that are unambiguously singular or plural, generating distractors is very straightforward. Let us assume that a given target ковёр *kovër* 'rug' results in the two morphological analyses in (2).

(2) a. ковёр+N+Msc+Inan+Sg+Nom
    b. ковёр+N+Msc+Inan+Sg+Acc

To generate the distractors, we strip the case tag and generate all six cases from that base by adding the tags (+Nom, +Acc, +Gen, +Loc, +Dat, +Ins). For the example at hand, this generates the following forms: ковёр, ковёр, ковра, ковре, ковру, ковром. Because the original token was singular, all of the generated wordforms are also singular.

The generated forms are combined with the original token, and a set of unique wordforms is supplied to the learners as options in the multiple-choice activity. Currently, all six cases are used as distractors every time, but insights from SLA and future research should make it possible to identify those subsets of distractors most facilitating learning given a specific target.

2.2 Stress

Russian stress patterns are specified lexically and cannot be predicted reliably from stem shape. Furthermore, many homographic forms of the same lemma have differential stress. This makes mastering the correct pronunciation of some words a difficult task for learners.

Four different activities were developed for stress. Unlike most 'highlight' activities in VIEW, the stress highlight activity does not make use of color, but simply adds a stress mark above every known stressed vowel in the text. For the 'click' activity, every vowel in the text becomes clickable: stressed vowels turn green and receive a stress mark; unstressed vowels turn red. The 'multiple-choice' activity selects some targets and learners try to identify the correctly stressed variant. The conventional use of the 'practice' activity is not well motivated for stress, since the entire set of possible responses is already represented in the 'multiple-choice' activity. Furthermore, typing stress marks is cumbersome for most users. Because of this, the 'practice' activity was replaced by an activity in which stressed vowels are highlighted when the cursor hovers over the token.

Target selection The morphological analyzer cannot always determine the stress of a given token. Sometimes this is because the lemma is not in the lexicon. Such tokens are never targeted, since their stress is not certain. Other times, the morphological analyzer is unable to completely disambiguate all of the readings of a given token. In such cases, the token can still be targeted if the remaining morphological ambiguity is immaterial with regard to stress. For example, the fact that the form stressed on the first syllable in (3-a) is ambiguous between accusative or nominative is not relevant in our context; what matters is that it can be distinguished from the genitive form in (3-b).

(3) a. гýбы
gúby
губа+N+Fem+Inan+Pl+Nom or +Acc
b. губы́
gubý
губа+N+Fem+Inan+Sg+Gen

Choosing targets for multiple-choice and practice activities is an interesting pedagogical issue, since almost every multisyllabic token is a potential target. Although there are many high-frequency words with difficult stress patterns, the overwhelming majority of Russian words have fixed stress. This means that if the program randomly selects targets for the multiple-choice and practice activities, many of the targets will not be pedagogically effective.

Since stress patterns in Russian are specified lexically, the solution to the target selection problem is also lexical. We compiled a stress activity target list of lemmas that have shifting stress based on our FST resource (Reynolds, 2014).[5] We also target one other large class of words: cognate words in L1 that have a different stress position in Russian. For example, compare English *rádiator* and Russian *radiátor*. We also added proper nouns for which a single standard stress position can be defined (e.g., *Rossíja* 'Russia', *Ukraína* 'Ukraine') to the stress activity target list.[6]

Distractor generation Generating distractors for the multiple-choice stress activity is very simple at this point. Since potential responses for a stress activity are a closed set, we provide all possible stress positions as distractors. Ideally, distractors should mimic likely incorrect responses that learners would make on a parallel cloze test. The distractors should represent the kinds of mistakes that learners typically make, so one could tune the distractor set by logging user interaction with the system, possibly also using distinct classes of learner models.

[5]For nouns, in addition to Zaliznjak's stress indexes *c*, *d*, *e*, and *f*, we also include masculine nouns with index *b* (end stressed), such as *kón' ∼kon'á* 'stallion'. For adjectives, only short-form adjectives are targeted.

[6]Many proper names have differential pronunciation for different referents, especially surnames: Ivánov vs Ivanóv. Such lemmas are not targeted.

2.3 Aspect

Most Russian verbs are either imperfective or perfective. For example, the English verb 'to say/tell' corresponds to the two Russian verbs *govorit'* (impf) and *skazat'* (perf). Imperfective verbs are generally used to express duration, process, or repetition. Perfective verbs are generally used for unique events, and they typically imply completion. The use of one aspect or the other is frequently dependent on context, as we discuss in more detail in a corpus study below.

Russian has a productive system of aspectual derivation, by which so-called aspectual pairs are formed. Although some verb pairs have no derivational relation (like *govorit'* / *skazat'*), many verb pairs have one of the following two relations:[7]

(4) a. IMPF: simplex verb ; PERF: prefix + simplex verb
smotret 'to watch.IMPF' / *po-smotret* 'to watch.PERF'
b. IMPF: (perfective stem) + suffix ; PERF: prefix + simplex verb
(ras-smatr)-ivat 'to examine.IMPF' / *ras-smotret* 'to examine.PERF'

Verbal aspect is arguably the single most challenging grammar topic for learners of Russian. The distinction between imperfective and perfective verbs is difficult for beginners to grasp, and even very advanced learners struggle to master the finer points. A set of ATICALL activities on aspect enables learners to focus on how aspect is used in context, which is crucial for Russian.

Target selection Since aspect in Russian is lexical, target selection also takes a lexical approach. First, not all verbs are paired with aspectual counterparts that have identical meanings. Since distractors should be equivalent in every respect other than aspect, we select only verbs that belong to an aspectual pair.[8] The list of paired verbs is compiled from three sources: 1) pairings such as (4-a) above are taken from the Exploring Emptiness database[9], 2) pairings such as (4-b) above are taken from Zaliznjak (1977), and 3) pairings without a derivational relationship (of which there are few) are extracted from electronic dictionaries.

Choice of verbal aspect is generally a matter of construal, i.e., how the speaker is structuring the discourse, and some verb tokens could be grammatically correct with either aspect. Consider the English examples *John saw Mary* and *John had seen Mary*. Even though they are likely to be used in different circumstances, both sentences are grammatically well-formed. Likewise, in Russian there are cases that allow either aspect. Meurers et al. (2010) suggested that lexical cues for English aspect and tense could be automatically identified by NLP. Indeed, many Russian grammars also indicate contexts in which one aspect or the other is impossible, or at least very unlikely. In order to identify contexts which constrain the expression of one aspect or the other, Russian grammar books were consulted, resulting in the following lexical cues.

(5) Contexts in which perfective aspect is impossible/unlikely:
a. Infinitive complement of *byt'* 'to be' (analytic future)
b. Infinitive complement of certain verbs (especially phrasal verbs, such as 'begin', 'continue', 'finish', etc.)
c. With certain adverbials denoting duration and repetition

[7] This is a simplistic sketch of Russian verbal aspect; for a proper discussion cf., e.g., Timberlake (2004).

[8] Although the notion of aspectual pairs has been shown to be somewhat problematic (Kuznetsova, 2013), this is the most robust approach available to us, and we do not expect problematic cases to be common.

[9] `http://emptyprefixes.uit.no`

(6) Contexts in which imperfective aspect is impossible/unlikely:

a. Infinitive complement of certain verbs (e.g., ‘forget’ and ‘succeed’)

b. With certain adverbials denoting unexpectedness, immediacy, etc.

A corpus study was conducted to test the usefulness of these features in an ATICALL application. The goal of the study was to determine the precision of the features, as well as their coverage, or recall. Precision was calculated as the percentage of verbs found adjacent to the appropriate lexical cues listed in (5) and (6) whose aspect was accurately predicted by that lexical cue. Recall was calculated as the percentage of all verbs whose aspect is correctly predicted by an adjacent lexical cue. From the perspective of ATICALL, precision tells us whether the student ought to know which aspect is required, which is useful for target selection. Recall tells us what percentage of verbs actually appear together with these lexical cues, and whose aspect is correctly predicted by them.

The study included two corpora, each investigated separately. The Russian National Corpus[10] (230 M tokens) is a tagged corpus with diverse genres. The annotation in the RNC frequently contains ambiguities, but since the aspect of Russian verbs is rarely ambiguous and the aspect of the contextual features is irrelevant, ambiguous readings do not significantly affect our outcomes. Since the RNC does not include syntactic relations, we rely on collocation of these lexical cues with verbs. SynTagRus[11] (860 K tokens) is a morphologically disambiguated and syntactically annotated dependency treebank of Russian. Because dependency relations are defined, identifying adverbial relations and verbal complements is straightforward. The results are given in Table 1.

	RNC	SynTagRus
Precision	0.95	0.98
Recall	0.03	0.02

Table 1: Results of the corpus study of lexical cues for aspect

The precision of these lexical cues is very high, meaning that when lexical cues are present, the verb is of the predicted aspect. This is expected, since known counterexamples such as (7) are uncommon. Given that Russian allows variable word order, it is surprising that collocation in the RNC is nearly as reliable as dependency relations in this task. Apparently these words have a very strong tendency to appear adjacent to one another.

(7)
Настоящий	друг	всегда	скажет	правду.
Nastojaščij	drug	vsegda	skažet	pravdu.
True	friend	always	will-tell.PF	truth

‘A true friend will always tell the truth.’

Unfortunately the recall of the lexical cues is extremely low. It correctly predicted the aspect of only one out of 50–60 verbs. Although future work is needed to explore these phenomena more thoroughly, these results seem to indicate that verbal aspect in Russian is predominantly determined suprasententially, with lexical cues playing only a very minor role.

[10] http://www.ruscorpora.ru/en/index.html

[11] http://www.ruscorpora.ru/search-syntax.html

For language learning, this result has several implications. First, it shows that learners can place their confidence in lexical cues, but these cues will not get them very far. Yet in some Russian textbooks, more space is dedicated to these lexical cues than to discourse considerations. This means that some learners may not be getting enough instruction on strategies that help in the majority of cases. Second, for the purposes of target selection, the Russian VIEW system can rely on lexical cues of aspect with some confidence. If a token is adjacent to the appropriate cues, then a learner should be expected to know the aspect of that token. However, since the lexical cues are so sparse, the system cannot make an intelligent decision for the overwhelming majority of verb tokens. One potential solution would be to implement machine-learning approaches to predict the distribution of each aspect more accurately. However, even though such models might make more accurate predictions, there is no guarantee that its output would reflect what a human second language learner should be capable of distinguishing.

If it is true that structural rules cannot provide adequate coverage of aspectual usage, then this implies that Russian verbal aspect is acquired through semantic bootstrapping. As learners are exposed to verbs of both aspects, real-world knowledge and expectations form the foundation upon which aspectual categories are built in their minds. If this is the case, it may not be feasible for an ATICALL system to predict how or whether the learner can be expected to know the aspect of a given target. The system can still provide a significant benefit to the learner by facilitating focus-on-form exercises, albeit blindly.

These last points are based on the assumption that the distribution of verbal aspect in Russian cannot be adequately accounted for with rules that are both pedagogically reasonable and technologically implementable. Our ongoing research will attempt to clarify this situation, but in the meantime, our system selects any paired verbs as targets, giving preference to forms that appear adjacent to our lexical cues.

Distractor generation Distractors for the multiple-choice activity are generated by replacing the lemma with its aspectual partner, and replacing the aspectual tag, as shown in (8-b).

(8) a. Original: читать+V+Impf+TV+Pst+Msc+Sg
b. Distractor: прочитать+V**+Perf**+TV+Pst+Msc+Sg

2.4 Participles

Russian has four kinds of adjectival participles, which are used both attributively and as relativizers. Their formation, meaning, and usage are not usually introduced to learners until more advanced levels. Although they are not used frequently in spoken Russian, participles are very common in written Russian, especially in high registers, such as literature, official documents, news, and technical writing. Many learners without parallel forms in their L1 struggle with Russian participles. All of these things make participles an excellent candidate for ATICALL visual input enhancement.

Target selection The four participles are present active, present passive, past active, and past passive. The passive participles are generally only formed from transitive verbs. Present participles are only formed from imperfective verbs, and past participles are typically formed from perfective verbs. The result of this is that not all verbs (or rather, verb pairs) can form every kind of participle. In order to select only those verbs from which a full 'paradigm' of distractors can be formed, we limit target selection to transitive verbs that are members of aspectual pairs (as described in section 2.3). We also do not target participles that have a possible lexicalized adjective reading, such as одетый *odetyj* 'dressed', or participles in the short-form.

Prompt generation Multiple-choice and cloze activities require a prompt for students to know which kind of participle is being elicited. One way to do this is to rephrase the participle using the relative determiner который *kotoryj* 'which'. For example, the present active participle дремлющий *dremljuščij* 'slumbering' can be rephrased as который дремлет *kotoryj dremlet* 'which/who slumbers'. Fortunately, it is possible to perform this rephrasing automatically, based solely on the tags of the original token. This is demonstrated in (9) and (10), where (a) gives an example of a participle in context, (b) gives the participle's grammar tags assigned by the tagger, and (c) provides the *relative-rephrase* and its readings. The bolded tags in (b) and (c) indicate the tags that are extracted from the participle reading in order to generate the relative-rephrase. The tags in (c) that are not bolded are the same for every participle of that category.

(9) Present Active

a. разлука есть гроб, заключающий в себе половину сердца
separation is tomb which-imprisons in itself half of-heart
'separation is a tomb which imprisons half of one's heart.'

b. заключающий: заключать+V+Impf**+TV+Prs**Act**+Msc+Sg**+Nom

c. который заключает 'which imprisons'
который+Pron+Rel**+Msc+Sg**+Nom
заключать+V+Impf**+TV+Prs**+**Sg**3

(10) Past Passive

a. Рассеянное молчание
which-was-scattered silence
'scattered silence'

b. рассеять+V**+Perf**+TV**+Pst**Pss**+Neu+Sg**+Nom

c. которое рассеяли 'which (they) scattered'
который+Pron+Rel**+Neu+Sg**+Acc
рассеять+V**+Perf**+TV**+Pst**+MFN+Pl

The given relative-rephrasing of passive participle in (10) is a zero person construction (неопределённо-личное предложение), in which there is no explicit subject, and the verb shows third-person plural agreement. Although this rephrasing is not always the best possible rewording of the passive, it is the alternative that works best in a wide variety of circumstances.

This method of prompt generation takes advantage of the systematicity of grammatical relations in Russian. It works because all of the morphosyntactic information needed to form the relative-rephrase is already present in the original participle's morphosyntactic tags.

3 Feedback

In contrast to Intelligent Tutoring Systems, ATICALL systems such as VIEW and reading support tools such as Glosser-RuG (Nerbonne et al., 1998), COMPASS (Breidt and Feldweg, 1997), REAP[12], or ALPHEIOS[13] focus on the analysis of authentic native text. Where input enhancement and reading support turns into exercise generation, such as the multiple-choice and cloze activities of VIEW, the feedback currently provided by the system is very limited. If a response is correct, then it turns green. If a response is incorrect, it turns red. VIEW does not attempt to reveal *why* a response is correct or incorrect. How about providing more informative adaptive feedback, whereby VIEW becomes more similar to an Intelligent Tutoring System?

In the following, we consider the degree to which the feedback that learners receive in an ATICALL environment can be enhanced without developing new NLP tools for learner language analysis. For the feedback methods listed below, enriched feedback can be provided using only the information already used in the target selection and distractor generation processes. In other words, the information used to select a given token is frequently the same information that is needed to provide enriched feedback beyond a simple correct/incorrect indicator.

3.1 Noun declension feedback (multiple-choice activity)

Feedback for noun declension activities can be based on dependency relations established by a native-language parser. For example, in the phrase *On obyčno sidel rjadom s mamoj* 'He usually sat next to (his) mother.INS', the word *mamoj* is in the instrumental case because it is the object of the preposition *s*. This fact is explicitly represented in a dependency tree, since the preposition *s* directly dominates *mamoj*. The ATICALL system can consult the parse tree to prepare relevant feedback. If a learner selects the wrong case for this target, then the preposition *s* is highlighted to show the learner why it should be in instrumental. As in tutoring systems, miniature lessons could be prepared for specific syntactic constructions to provide related information. For example, with this preposition, the learner could be presented with the following: "*s* can govern three different cases depending on its meanings: INS='with', GEN='(down) from', and ACC='approximately'. (Use with ACC is rare.)"

This type of feedback is relevant, informative, and can easily be linked to specific syntactic constructions. Effective adaptive feedback in such a multiple-choice activity thus does not depend on learner-language NLP. The native-language NLP – both syntactic analyses and distractor generation – is providing effective feedback capabilities, even if it is not equivalent to what is possible with learner-language NLP.

3.2 Stress feedback (click and multiple-choice activities)

In the multiple-choice and practice activities for stress, targets are selected according to the stress activity target list introduced in section 2.2, which is extracted from the FST source files (Reynolds, 2014) partially based on Zaliznjak (1977). In his dictionary, every word is assigned a code signifying which stress pattern it belongs to. We combined this information with frequency data from the Russian National Corpus in order to select an exemplar for each stress type. Based on this information, a tooltip can be displayed that shows the exemplar and its paradigm when a learner gives an incorrect response. In this way, the learner is able to associate the targeted token with a word that is hopefully more familiar. This type of feedback supports both top-down and bottom-up learning, since it relies on an abstract connection to a concrete example.

[12]`http://reap.cs.cmu.edu`
[13]`http://alpheios.net`

3.3 Aspect feedback (multiple-choice activity)

As we discussed in section 2.3, determining *why* a given aspect is required in a given context is rarely possible with current technology. However, some tokens do have a clear lexical cue, which is used both to promote their selection as targets, and can also be used as corrective feedback. For example, given the sentence *On obyčno sidel rjadom s mamoj.* 'He usually sat.IMPF next to (his) mother', if the learner selects the perfective verb, then the adverb cue *obyčno* can be highlighted to show the learner *why* perfective is not appropriate. As in the previous case, the information needed to give enhanced feedback is the same information used in target selection.

3.4 Participles feedback (multiple-choice activity)

Recall that the participle activities discussed above have a prompt provided in the form of a *kotoryj* 'which/who' relative-rephrase of the participle. It was shown that the morphosyntactic properties of the participle correspond directly to the morphosyntactic properties of the relative-rephrase. These very same relations can be leveraged to provide feedback to the learner.

For example, let us say that the original token was a past active participle *napisavšij* 'who wrote' with the relative-rephrase hint (*kotoryj napisal*). If the learner selects the present active participle distractor *pišuščij*, they could be presented with feedback such as: "The word you selected means *kotoryj pišet*. Pay attention to the tense of *napisal*." This feedback is tailored to the learner's response, and encourages the learner to compare the functional meanings of the relevant morphological forms. In this case, the strategy used for prompt generation facilitates customized feedback.

Overall, the four examples sketched above show that the provision of specific types of adaptive feedback is a meaningful and natural extension of an ATICALL system such as VIEW, using the same NLP techniques employed in analysis, target selection and distractor generation. We are currently working on extending the implemented Russian activities discussed in section 2 in this direction.

4 Conclusions and Outlook

We reported practical and theoretical issues related to developing automatic visual input enhancement for Russian, with a focus on including adaptive feedback in such an ATICALL system. The selected topics demonstrate the challenges that a morphology-rich language brings with it and how a rule-based morphological analysis can be used to tackle them. In addition to providing the means for effective disambiguation, the finite state approach makes it possible to generate wordforms for distractors, prompts (participles), and stressed wordforms. We also characterized certain types of adaptive feedback, typically associated with intelligent language tutoring systems, that can be added in an ATICALL environment using the same information that is used for target selection and distractor generation. This refines the perspective distinguishing two subdisciplines of ICALL (Meurers, 2012), while keeping a clear distinction on the processing side between analyzing learner language and analyzing native language for learners.

In terms of future work, the crucial next step is to empirically evaluate the approach and the specific parameterization (activities, enhancement methods, distractors, and feedback used) in terms of learner uptake and, more generally, learning gains. While identifying a real-life educational context in which the tool can be integrated meaningfully is a complex undertaking, the computational approach presented in this article should readily support a controlled study with different intervention groups and a standard pretest-posttest-delayed posttest design. The foundational hypotheses upon which visual input enhancement is built have not been empirically evaluated to a sufficient degree (Lee and Huang, 2008), so evaluating learner outcomes is needed not only to establish the system's effectiveness, but also to validate the theories upon which it is based. As already suggested in Meurers et al. (2010), an ATICALL platform such as VIEW should make it possible to push intervention studies to a level where effects could be more readily established than in the very controlled but small laboratory settings.[14] This seems particularly relevant since there are many parameters that need to be explored, e.g., which kind of visual input enhancement works for which kind of learners and for which kind of linguistic targets presented in which contexts. We are also interested in exploring which kind of distractors (and how many) are optimal for which activities or learner levels. Finally, while it is beyond the current analysis we perform, we plan to investigate different ways of measuring *noticing* through computer interaction behaviors, and test their correlation with individual learner characteristics and learning outcomes.

On the computational side, we also plan to evaluate the performance of the NLP components used in the approach in terms of precision, recall, and speed. Here it is important to evaluate not only the general performance, but also its performance for the specific parts of speech and morphological properties that are at issue in a given activity. For the activities discussed in this article, this includes nouns for the noun declension activity, infinitive and indicative verbs for the aspect activity, participles for the participles activity, and all parts of speech for the stress activity. The performance should also be tested on different genres and reading levels, since those distinctions will affect NLP performance. Ideally, the performance should be analyzed on a corpus that is characteristic of the material that the learners or their teachers select as basis for generating activities – which is only possible in an interdisciplinary approach including both NLP research and real-life teaching and learning contexts.

In terms of making an ATICALL system useful in real-life, an important challenge arises from the fact that many texts do not contain enough of the relevant sorts of targets or contextual cues. This, for example, was apparent in the corpus study related to verbal aspect. The texts a learner chooses for enhancement and activity generation thus should be filtered in a way ensuring a sufficient number of targets in the texts. To address that need, we plan to further develop language-aware search engines (Ott and Meurers, 2010) supporting the selection of appropriate materials.

Acknowledgments

We would like to thank Elena Grishina and Andrej Zaliznjak for making the most recent version of Zaliznjak's grammar dictionary available electronically for academic purposes. We are grateful to Laura Janda and the CLEAR research group at the University of Tromsø, as well as two anonymous reviewers for their comments on our paper. All remaining faults are, of course, our own. In terms of the context making our collaboration possible, we are indebted to Trond Trosterud and Lene Antonsen at the Giellatekno research group at the University of Tromsø.

[14]In a similar vein, Presson et al. (2013) discuss the potential of experimental computer-assisted language learning tools for SLA research.

References

Amaral, L. and Meurers, D. (2011). On using intelligent computer-assisted language learning in real-life foreign language teaching and learning. *ReCALL*, 23(1):4–24.

Breidt, E. and Feldweg, H. (1997). Accessing foreign languages with COMPASS. *Machine Translation*, 12(1–2):153–174. Special Issue on New Tools for Human Translators.

Dickinson, M. (2010). Generating learner-like morphological errors in Russian. In *Proceedings of the 23nd International Conference on Computational Linguistics (COLING-10)*, Beijing.

Dickinson, M. and Herring, J. (2008a). Developing online ICALL exercises for Russian. In *The 3rd Workshop on Innovative Use of NLP for Building Educational Applications (BEA-3) at ACL'08*, pages 1–9, Columbus, OH.

Dickinson, M. and Herring, J. (2008b). Russian morphological processing for ICALL. In *The Fifth Midwest Computational Linguistics Colloquium (MCLC-5)*, East Lansing, MI.

Gorisev, S., Koynov, A., Kuzemchik, V., Lisinin, S., Mikhaleva, E., Mishunin, O., Savinov, A., Terekhin, D., Firstov, D., and Cherkashin, A. (2013). Интеллектуальный лингвопроцессорный комплекс «КЛИОС» для обучения РКИ [Intelligent language-aware tutoring system "KLIOS" for studying Russian as a foreign language]. Современные проблемы науки и образования *[Modern problems of science and education]*, 6.

Karlsson, F., Voutilainen, A., Heikkilä, J., and Anttila, A., editors (1995). *Constraint Grammar: A Language-Independent System for Parsing Unrestricted Text*. Number 4 in Natural Language Processing. Mouton de Gruyter, Berlin and New York.

Karpov, N., Baranova, J., and Vitugin, F. (2014). Single-sentence readability prediction in Russian. In *Proceedings of Analysis of Images, Social Networks, and Texts conference (AIST)*.

Koskenniemi, K. (1983). Two-level morphology: A general computaitonal model for word-form recognition and production. Technical report, University of Helsinki, Department of General Linguistics.

Kuznetsova, J. (2013). *Linguistic Profiles: Correlations between Form and Meaning*. PhD thesis, University of Tromsø. Doctoral Dissertation.

Lee, S.-K. and Huang, H.-T. (2008). Visual Input Enhancement and Grammar Learning: A meta-analytic review. *Studies in Second Language Acquisition*, 30:307–331.

Meurers, D. (2012). Natural language processing and language learning. In Chapelle, C. A., editor, *Encyclopedia of Applied Linguistics*, pages 4193–4205. Wiley, Oxford.

Meurers, D., Ziai, R., Amaral, L., Boyd, A., Dimitrov, A., Metcalf, V., and Ott, N. (2010). Enhancing authentic web pages for language learners. In *Proceedings of the 5th Workshop on Innovative Use of NLP for Building Educational Applications (BEA-5) at NAACL-HLT 2010*, pages 10–18, Los Angeles.

Nerbonne, J., Dokter, D., and Smit, P. (1998). Morphological Processing and Computer-Assisted Language Learning. *Computer Assisted Language Learning*, 11(5):543–559.

Nozhov, I. (2003). Морфологическая и синтаксическая обработка текста (модели и программы) *[Morphological and Syntactic Text Processing (models and programs)] also published as* Реализация автоматической синтаксической сегментации русского предложения *[Realization of automatic syntactic segmentation of the Russian sentence].* PhD thesis, Russian State University for the Humanities, Moscow.

Ott, N. and Meurers, D. (2010). Information retrieval for education: Making search engines language aware. *Themes in Science and Technology Education. Special issue on computer-aided language analysis, teaching and learning: Approaches, perspectives and applications*, 3(1–2):9–30.

Presson, N., Davy, C., and MacWhinney, B. (2013). Experimentalized call for adult second language learners. In Schwieter, J. W., editor, *Innovative Research and Practices in Second Language Acquisition and Bilingualism,* pages 139—-164. John Benjamins.

Reynolds, R. (2014). A two-level finite-state transducer for Russian language-learning applications. `https://victorio.uit.no/langtech/trunk/langs/rus/`.

Rutherford, W. E. and Sharwood Smith, M. (1985). Consciousness-raising and universal grammar. *Applied Linguistics*, 6(2):274–282.

Schmidt, R. (1990). The role of consciousness in second language learning. *Applied Linguistics*, 11:206–226.

Segalovich, I. (2003). A fast morphological algorithm with unknown word guessing induced by a dictionary for a web search engine. In *International Conference on Machine Learning; Models, Technologies and Applications*, pages 273–280.

Sharoff, S., Kopotev, M., Erjavec, T., Feldman, A., and Divjak, D. (2008). Designing and evaluating a Russian tagset. In *Proceedings of LREC*, Marrakech.

Sharwood Smith, M. (1993). Input enhancement in instructed SLA: Theoretical bases. *Studies in Second Language Acquisition*, 15:165–179.

Timberlake, A. (2004). *A reference grammar of Russian*. Cambridge University Press.

Vygotsky, L. S. (1986). *Thought and Language*. MIT Press, Cambridge, MA.

Zaliznjak, A. A. (1977). Грамматический словарь русского языка: словоизменение: около 100 000 слов *[Grammatical dictionary of the Russian language: Inflection: approx 100 000 words].* Изд-во “Русский язык”.