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How Tutoring Policies Affect the Tutoring Strategies Used by Expert Tutors

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We analyzed the tutoring strategies in nine two-hour long tutoring sessions in which Joel Michael and Allen Rovick, Professors of Physiology at Rush Medical College, tutored first year medical students with the goal of helping them learn to solve problems involving the baroreceptor reflex. These sessions were carried on keyboard-to-keyboard with tutor and student in separate rooms communicating over a telephone link, in order to simulate the conditions under which students use the system. Current intelligent tutoring systems using cognitive models of the student have utilized their student models to determine **what** subject areas to focus on in a tutorial session, but have not adjusted **how** they tutor. Cho has shown, however, that expert tutors dynamically adjust their tutoring policies in response to changes in their assessments of student abilities (Cho, Michael, Rovick, & Evens, 2000). In order to implement this kind of policy change in our ITS, CIRCSIM-Tutor, we needed to ascertain whether tutors select different lower level strategies to carry out different higher level policies.

Cho (Cho et al., 2000) observed two different tutoring policies in nine two-hour sessions. In the *Immediate Feedback* (IMF) *Policy*, the tutor helps the student solve the problem step by step, commenting immediately on every student input, good or bad. In the *V2 Policy,* designed by the two expert tutors for use in our ITS, the tutor attempts first to build up a model of the student's understanding, by asking the student to predict the qualitative changes in seven important variables in one phase of the baroreceptor reflex, and then gears tutoring to correcting any errors that the student makes.

Michael and Rovick planned the series of keyboard tutoring sessions studied here to provide us with samples of tutoring language using the V2 policy. Cho et al. (2000) observed that the tutors, nevertheless, sometimes abandoned the V2 policy in favor of IMF. Comparing these policy switches with student assessments, Cho discovered that switches from V2 to IMF occurred when the student made a number of consecutive errors, while switches from IMF back to V2 occurred at the beginning of a new phase after the student started to perform better.

We hypothesized that the IMF policy, preferred by expert tutors for students performing poorly, would employ more strategies that help the student move through the problem solving process: such as Prompt-Start, Move-Forward, and Logical-Order, while the V2 policy would employ more sophisticated tutoring strategies. We also expected to see a larger number of strategies in each IMF tutoring phase.

Before the study started we divided the two-hour sessions studied by Cho into 245 separate sections, bounded by strategy changes. Then Lulis and Evens separately classified the strategy in each section with agreement on 235 sections and disagreement on 10. An inter-rater reliability study yielded a Cohen's kappa of 0.95.

As we expected, several of the strategies that require more sophisticated understanding from the student are more frequent under V2. For example, there were 11 examples of tutoring via analogy under V2 and only 2 under IMF. Applying Fisher's Exact Test yields $p<0.05$.

Our hypothesis that the Move-Forward strategy would be more frequent under IMF was supported. There were 75 in the 15 IMF phases (a mean of 5 per phase), but only 15 in the 31 V2 phases (giving a mean of 0.48); using a one-sided t-test with unequal variances this difference is highly significant with $p<0.0001$. There were five examples of T-prompts-start under IMF, but none under V2; this difference is significant with $p<0.05$. Finally, there were 6 examples of T-tutors-logical-order under IMF and only 3 under V2. The t-test gives significance with $p<0.05$.

Tutoring a phase under IMF takes longer in that many more tutoring strategies were deployed when this policy was in use. The average number was 9.06 per tutoring phase vs. 3.19 per phase for the V2 policy and a t-test showed that this difference was significant at the 0.0001 level ($p=3.57\times10^{-8}$). These results clearly show that expert tutors change their lower-level strategies when their high-level policy changes, in response to changing student assessments.

Acknowledgments

References

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