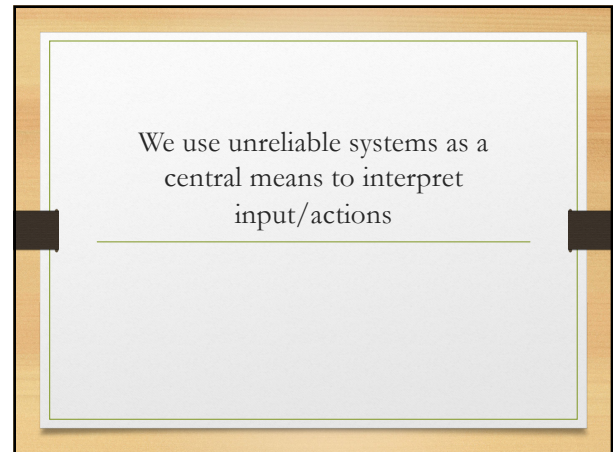
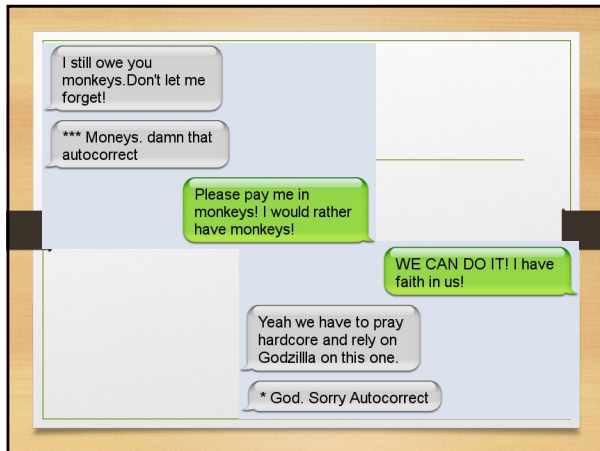




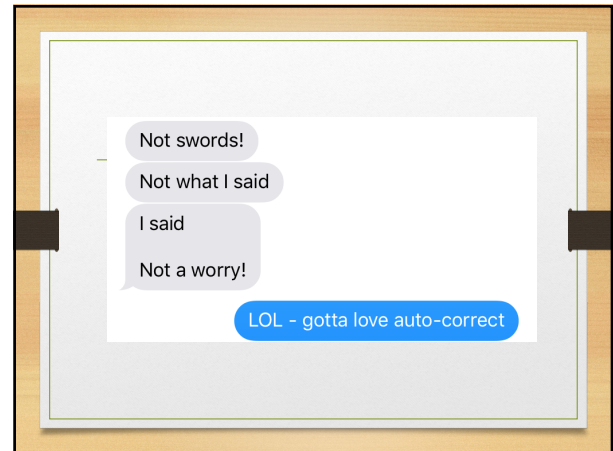
1



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3



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5



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## Fix?

- Better technology
- Yes, **BUT**
  - Language is ambiguous
  - Gestures are ambiguous
  - World is (too) varied
- Human-in-the-loop required
- Potential legal issues



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## Complementary approach

- Better understanding of human interaction with unreliable systems
- Study perceptual, cognitive & physical aspects
- Create new UI technologies



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## Fixing errors - simple?

- Notice error
- Decide if it is worth fixing
  - Ecological rationality
- Figure out how to correct
- Correct it

**Errors can happen at every step!**

**Errors on errors** 😞

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## Analyze human behaviours around occasionally failing systems

- Text entry
- Gesture recognition

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## Solution?

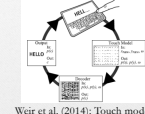
- Partial



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## State-of-the-art Auto-correction

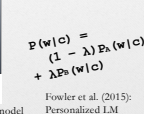
- Much research has been done to improve text entry, e.g.:



Weir et al. (2014): Touch model



Goel et al. (2012): Walking model



Fowler et al. (2015): Personalized LM

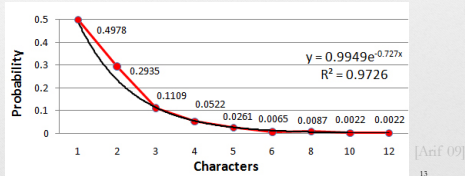
$$P(w|c) = (1 - \lambda) P_h(w|c) + \lambda P_p(w|c)$$

- However, even best approaches have error rates of ~5%
  - Higher for specific individuals and situations
  - Cannot be reduced to 0% due to ambiguity of language

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### Model of effect of text entry errors

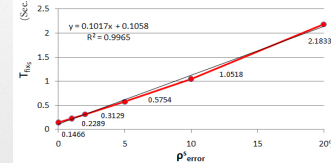
- How should errors affect correction times?
- Probability of noticing errors (only Backspace)



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### Model of effect of text entry errors

- Time to fix if system error increases?



- Nonlinear due to errors on errors

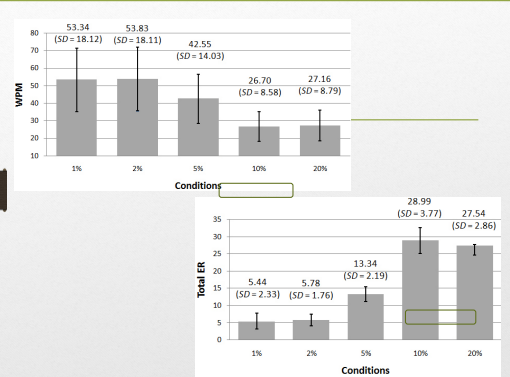
14

### Experiment

- Text entry with "faulty" keyboard
  - Adjacent key with controlled failure rate
  - 1, 2, 5, 10, 20% errors

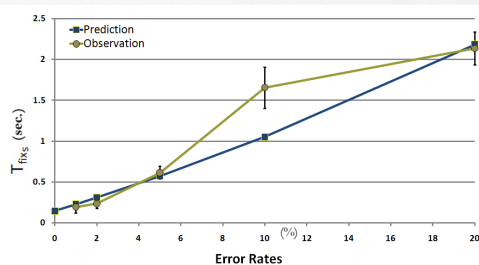


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### Model Validation



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### Adaptation

- Errors can happen repeatedly
- Humans can adapt
- Rely on human adaptation?
- OK if technology is predictable
- BUT...



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## Adaptation: Core problem

- Technology not always predictable
  - Recognition tech sensitive to "random" variations
  - Changes due to updates/upgrades/...
- People don't generally understand underlying systems
- Underlying system appear random
  - So we cannot predict if & when they will fail
  - Can't adapt to failures

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## Research Questions

- Do users adapt to a faulty system?
- What influences this adaptation process?

[Anif GI 14]

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## Research Questions

- Do users adapt to a faulty unistroke gesture recognizer?
- What influences this adaptation process?

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## Research Questions

- Do users adapt to injected misrecognition errors of a unistroke gesture recognizer?
- What influences this adaptation process?

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## Research Questions

- Do users adapt to injected misrecognition errors of a unistroke gesture recognizer by switching to an alternative gesture set?
- What influences this adaptation process?

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## Errors in Gesture Recognition

- Generally error-prone
  - Useful when at least 97% accurate [LaLomia, 1994]
  - Abandoned when below 40% [Karam & schraefel, 2006]
- Usually compare performed with existing
  - Misrecognition error
    - Most common
  - Failure to recognize (! library, accidental strokes)

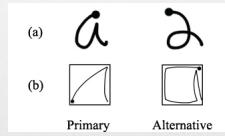
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## Alternative Gestures

- Many support several drawing variations

- Alternatives:
  - Less intuitive
  - Harder to discover



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## Apparatus

- \$1 unistroke recognizer [Wobbrock et al., 2007]
  - 7 templates / letter
  - 99% accuracy rate (.7% misrecognition, .3% failure to recognize)
- Multistroke allows many variations
  - Difficult to identify human errors
  - Users require time to identify an issue

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## Supported Gestures

- Graffiti more intuitive



- Graffiti  $\approx$  Unistrokes [Castellucci, MacKenzie, 2008]
  - Method switch will not compromise performance

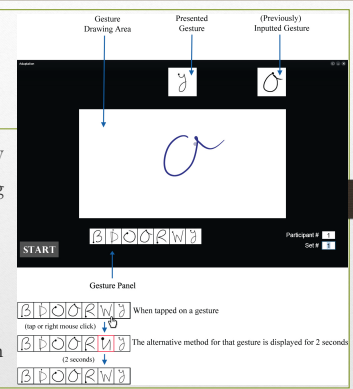
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- Discoverability
- Error handling



- Synthetic misrecognition



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## Study 1 – 0-30%

- 12 novice participants
- Practice: 5/Graffiti gesture
- 7 letters – 630 times
  - 3 random Graffiti with 10, 20, 30% injected misrecognitions
- Alternative gesture use was not forced
  - No error injection on 1+ attempts

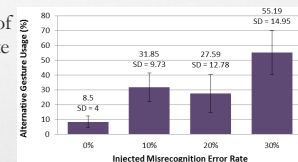


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## Alternative Method Usage

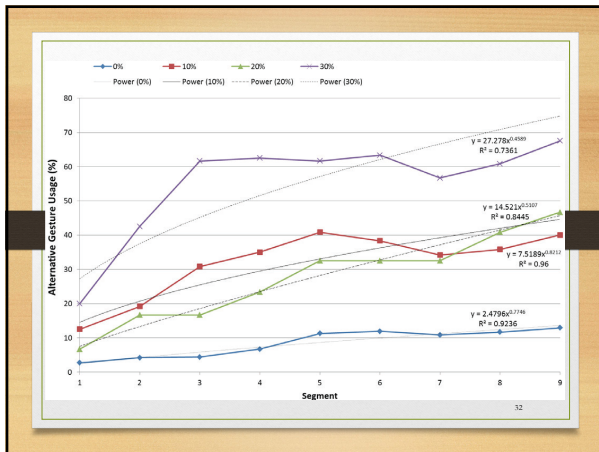
- Significant effect of misrecognition rate



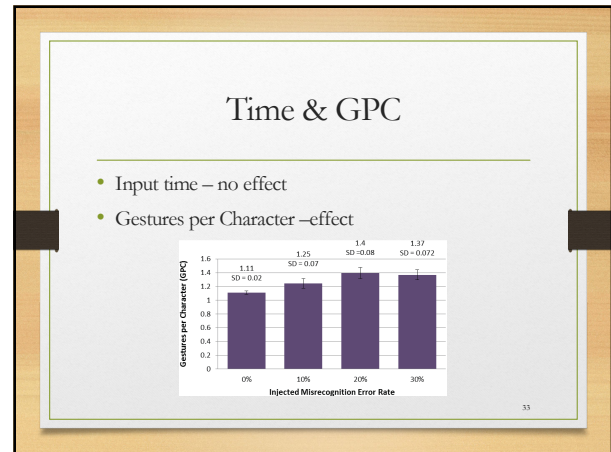
- 0, 10-20, 30% significantly different

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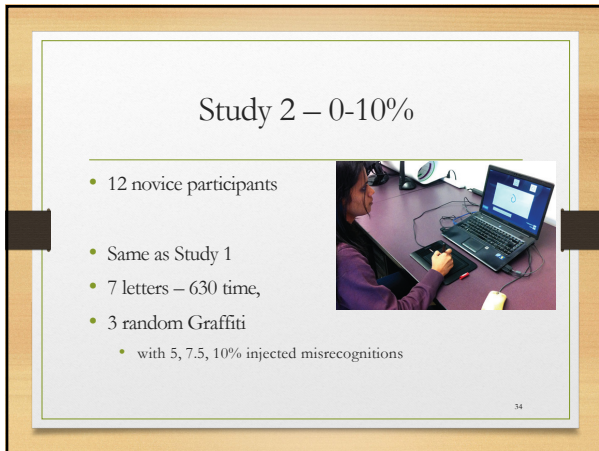
31



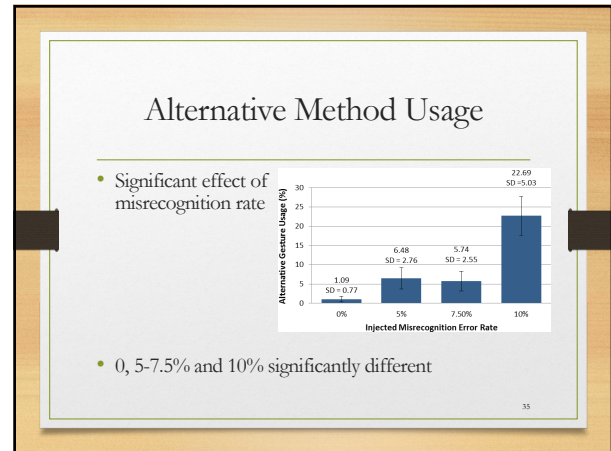
32



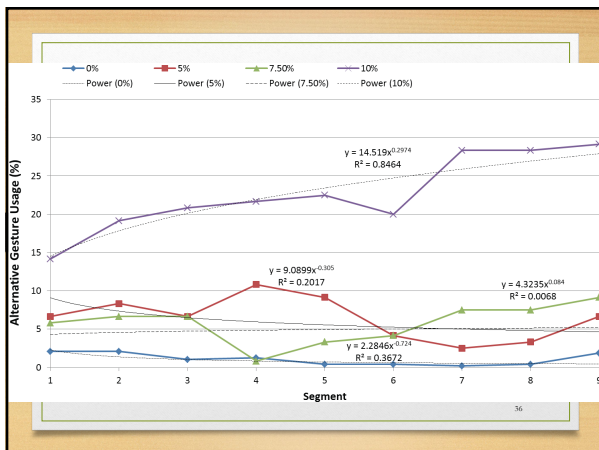
33



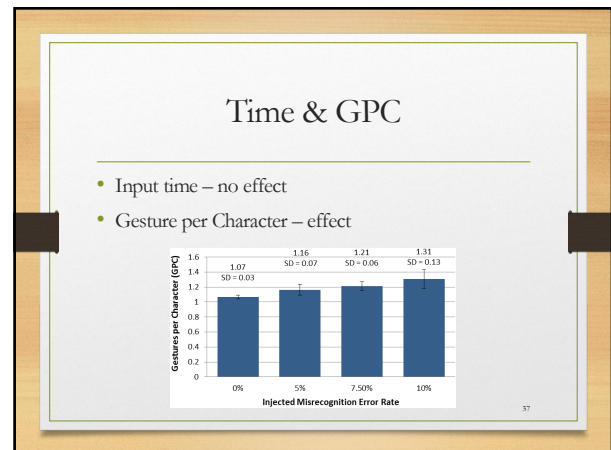
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## Outcomes & Recommendations

- Users can adapt to a faulty gesture recognizer
- Adaptation depends on injected error rate
  - Similar trends in psychology, skill acquisition, UI
    - Greater effort = more recall-based actions
- More than 90% accuracy rate is necessary
- Users must have options
- Alternates should be easy to discover

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## Further Discussion

- Some adaptation for 0% as well
- Half did not identify all 3 faulty letters
  - Or did not spend effort to learn
  - Different cognitive strategies / personalities?



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## Adaptation

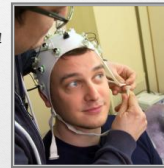
- Do humans adapt?
  - Yes
  - BUT
    - Only to things they *notice*
    - Sufficiently frequently
    - And reliably
  - ALSO
    - Benefit needs to be high enough



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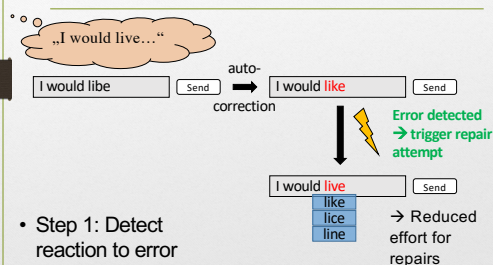
## Is noticing errors enough?

- Sense reaction to errors
  - Error-Related Potential in EEG signal!
- Brain-computer interface to sense user reactions to incorrect auto-corrects
- (Trigger better system responses by offering different corrections)



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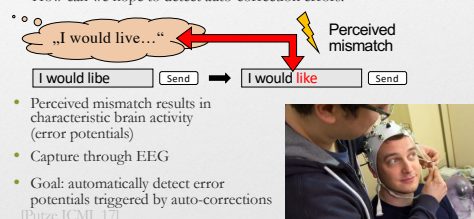
## Self-Repairing Auto-Correction



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## Error Potentials

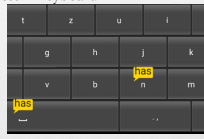
- How can we hope to detect auto-correction errors?
  - Perceived mismatch results in characteristic brain activity (error potentials)
  - Capture through EEG
  - Goal: automatically detect error potentials triggered by auto-corrections [Putze ICMI 17]



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## Experimental Paradigm

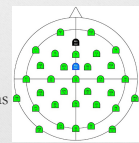
- Android tablet text entry app with custom keyboard
- Dictionary-based auto-correction
  - Select replacement randomly from entries with minimal edit distance
- User has to notice errors → Draw attention to auto-corrections
  - Audio-tactile cue
  - Multiple visual cues at potential gaze targets
- Rigged keyboard (forced 5% switched characters)
  - Increase number of correction events in limited time frame



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## Data Collection

- 12 participants
- Typed 120 sentences (+15 training) for about 23 minutes
  - Sentences from OpenSubtitles phrase set
- Questionnaire on typing behavior and self-assessment
  - Validated people noticing auto-corrections
- Recorded EEG data at 32 electrode positions + synchronized user's typing behavior

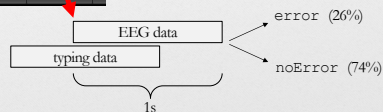


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## Classification Approach



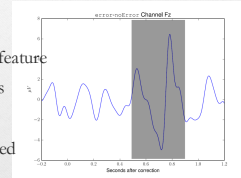
For each auto-correction, classify data based on correction success



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## EEG Features

- For each EEG electrode:
- Use filtered, down-sampled EEG signal as time-domain feature
- Use power spectral density as frequency-domain feature
- Both types of features carry information about event-based EEG patterns
  - May be contaminated with artifacts: user moving, gazing, typing



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## Context Features

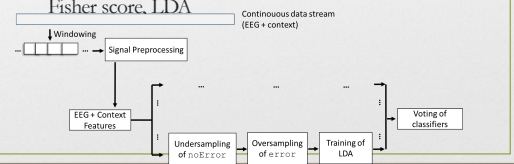
- User behavior and input characteristics contain relevant information
- Two types of context features:
  - 1) Encode likelihood of auto-correction error
    - Length of the replaced word (# characters)
    - # candidate words of minimal edit distance
  - 2) Encode likelihood of user perceiving error
    - Typing speed for replaced word relative to average typing speed
    - Time before user continues typing during EEG window (in ms)



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## Classification

- Data set unbalanced ( $\#noError > \#error$ )
  - Handle by oversampling & undersampling + bagging
- For each subsample: Feature selection based on Fisher score, LDA



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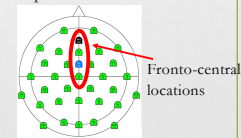
## Classification Results

		Accuracy	Precision	Recall	F1 Score
Baseline	Mean	0.74	-	-	0.38
EEG	Mean	0.69	0.25	0.38	0.30
	SD	0.08	0.10	0.13	0.07
Context	Mean	0.81	0.40	0.70	0.49
	SD	0.03	0.19	0.25	0.18
Combined	Mean	<b>0.85</b>	<b>0.82</b>	<b>0.65</b>	<b>0.72</b>
	SD	0.03	0.05	0.11	0.08

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## Feature Interpretation

- For every person, ~6 features were selected in 75% of all folds and subsamples → stable intra-personal
- Across all persons, ~16 features selected in more than 40% of all folds and subsamples → stable inter-personal
- Plausible features:
  - Does not rely on ocular artifacts



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## Discussion

- Auto-correction errors can be detected!
  - From EEG and context features
- Step 2: Work in progress
  - Challenge: classification window alignment
    - Delay in perception?
    - Include eye tracking?
  - Good enough to improve text entry efficiency?

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## Better UIs for Occasionally Failing Technology

- Better understanding of human interaction with unreliable systems
- Study perceptual, cognitive, & physical aspects
- Create new UI technologies



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## Bigger Issues

- Can we eliminate all failures?
  - World extremely complex
  - Legal issues
- Overreliance on automation
  - Automation bias
- Ecological Rationality
- Misperception of probabilities



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## Future work

- Improvements to text entry [Alharbi GI 19]
  - Better error visualizations & correction methods
- EEG-based active auto-correct
- Auto-correct in scheduling
- Voice recognition correction
- Address misperception of probabilities
- ...

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