VIRTUAL REALITY BASED END-USER ASSESSMENT TOOL for Remote Product /System Testing & Support

PRESENTATION OUTLINE

- **AIM OF RESEARCH**
- MOTIVATIONS
- *** BACKGROUND & RELATED WORK**
- ANALYSIS APPROACH
- *** MODEL ARCHITECTURE**
- *** EXPERIMENT & RESULTS**
- CONCLUSION

MOTIVATIONS

❖DESIGN

- WOULD USERS APPRECIATE THE PRODUCT?
- CAN THEY USE IT EASILY WITH MINIMAL EFFORT?

MAINTENANCE & TRAINING

- GIVING THE RIGHT TRAININGS?
- CAN IT BE ASSEMBLED/DISASSEMBLED FOR MAINTENANCE PURPOSES?

MOTIVATIONS



- WOULD USERS APPRECIATE THE PRODUCT?

OBSERVATIONAL DATA
COLLECTED FROM THE USER
PRODUCT INTERACTION MAY
REVEAL ANSWERS FOR THESE
QUESTIONS

MAINTENANCE PURPOSES?

COLLECTION OF OBSERVATIONAL DATA

- I. USE OF PHYSICAL PROTOTYPES
 - EXPENSIVE
 - TIME CONSUMING
 - GEOGRAPHICALLY RESTRICTED APPLICATION AREA

II. USE OF VIRTUAL PROTOTYPES & AUTOMATED ANALYSIS

- INEXPENSIVE
- FAST
- MORE DETAILED DATA COLLECTION FLEXIBILITY

MOTIVATIONS

A VR BASED END USER ASSESSMENT TOOL



- >IDENTIFY PROBLEMATIC ASPECTS
- REVEALS USERS' PERFORMANCE
- >SHOWS PATHS FOLLOWED BY USERS & HOW THEY DIFFER FROM DESIGNER EXPECTATIONS
 - >REPORTS SIMILARITIES & DIFFERENCES
 AMONG USERS

OBJECTIVE

To design a VR based automated tool to filter, analyze and interpret behavioral data

without compromising from scale and efficiency?

APPROACH

We propose integrating existing virtual reality technology with an automated behavioral data analysis approach:

- Construct VR <u>based prototype testing simulations</u> to capture human interaction in log-files
 - a prototype, digital mock-ups (DMUs)
 - an assembly
 - a maintenance scenario
- II. Develop an intelligent and automated data analysis technique to extract useful qualitative and quantitative information from voluminous raw data

Virtual Reality

Virtual Reality in Design & Maintenance

- ≥3D visualization
- ➤Interactive simulations

Today successful applications of VR include:

- ➤ Product prototyping for testing
- ➤ Training: in medicine, military and manufacturing
- ➤ Maintenance, human factors and ergonomic studies
- Furniture industry, architecture, interior design









Maintenance

Training in Medicine

Training in Manufacturing

Architecture



RELATED WORK

Virtual Reality

Are Virtual Prototypes reliable for testing purposes?

- ❖The predictive power of virtual-prototypes is almost the same as physical prototypes (Dahan et al., 1998)
- ❖VR features offer users the opportunity to explore virtual objects at a high level of detail that are appropriate for activity evaluation (Hurwicz, 2000)
 - Gamberini et al. (2003) conclude that people show realistic responses to dangerous situations simulated in VR
 - Training using computer models reported to be more effective, compared with the traditional classroom lectures (Fletcher, 1996)
- ❖VR and other related technologies allow for complete recording, prevents loss of important user data compared to traditional pen-pencil based observational methods (Kempter et al., 2003)

Automated Analysis of Data



Human-Computer Interaction

capturing user's interactions is very straightforward, analysis is difficult since user interface events are very detailed and large in volume



Usability Engineering

- Data collection & Recoding
- Counts, metrics, statistics
- Searching sequences in data
- Comparing sequences
- Sequence extraction
- Visualization



Data Mining

knowledge-discovery in large volumes of data

Automated Analysis of Data





Human-Computer Interaction

capturing user's interactions is very straightforward, analysis is difficult

Data Mining

knowledge-discovery in large volumes of data

since user interface events

are very detailed and la What is meant by usability?



- ✓ Perform main functions
- ✓ Efficiency
- ✓ Ease of learning
- ✓ Being error-proof and reliable

Usability Engineeria ✓ Feelings of user

- ❖Data collection & R
- Counts, metrics, stat
- Searching sequences in data
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Automated Analysis of Data





Human-Computer Interaction

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❖Data collection & R

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- ✓ Perform main functions
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Data Mining

knowledge-discovery in large volumes of data



- Statistical Methods
- - ✓ Ease of learnin(❖ Prediction techniques,
 - Markov processes
 - Sequential pattern mining techniques
 - Clustering
 - Factor analysis

RELATED WORK

Automated Analysis of Data

Human-Computer Interaction

MACSHAPA, Sanderson et al. (1994)

- spreadsheet format & pattern matching by aligning the actual logs
- visual representation of data & statistical reports

USINE, Sanderson et al. (1994)

- statistical reports
- log comparison search for violations, cancellations etc.

Smart Agents, Hilbert and Redmiles (1998)

• modules that create a report in case of an unexpected user behavior

Maximal Repeating Patterns, Siochi and Ehrich (1990)

detect frequent patterns in sequence of events

Data Mining

Data mining system for drop test analysis of electronic products (Zhou et al., 2001)

Data mining in software metrics (Dicks et al.,2004)

Mining Customer support call tracking database, Muehleisen (1996)

PROBLEM REQUIREMENTS

i. AUTOMATED DATA COLLECTION

Capturing user interaction with virtual product or system in log files

ii. AUTOMATED ANALYSIS

- What are the problematic points that affect performance and satisfaction?
- What are the paths users follow to accomplish certain tasks in the system?
- Do the paths followed by different users match with designer's expectations and with each other?
- What are the patterns that deviate from expected process model?
- How high is the performance of users with the system? Does it conform to expected standards?
- What are the performance characteristics of users following a certain path?

TO ANSWER THESE QUESTIONS WE PROPOSE A FOUR-PHASE APPROACH...

ANALYSIS APPROACH

PHASES

- 1. Record user interaction with the system as set of events
- 2. Determine metrics that are indicators of performance in the system Ex: Task Completion Times, Cancelled Tasks, Repeated Tasks...

Calculating these values for each user

Using statistical techniques and/or other measurements

- 3. Cluster users with respect to the metrics
- 4. Extract followed paths in each cluster Compare these paths with the designer data and other user clusters

Expert Logs

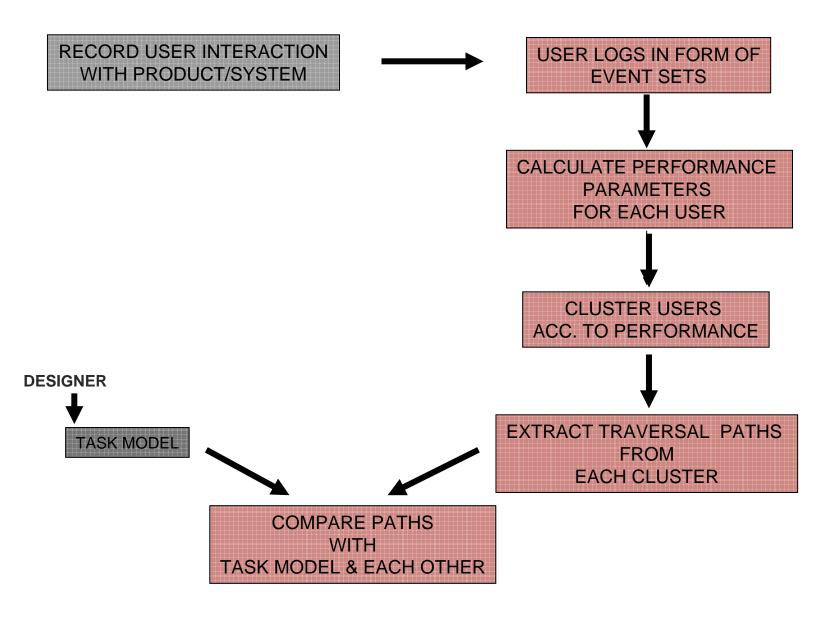
Process Model

OUTCOME

<u>Designed VR based</u> Behavioral Data Analysis Tool

- Reveals problems in the design
- Suggests more efficient design & training options
- Compare alternatives in terms of usability

MODEL ARCHITECTURE



PHASE I

Capturing User Interaction With The System

For each session, record:

- All user input and system output as a set of events
 - II. Necessary measurements as set of measured attributes in log files



$$R_i = \langle (i), (e_1, e_2, \dots, e_n), (a_1, a_2, \dots, a_m) \rangle$$

OUTPUT OF PHASE 1

Log files of subjects

Log file for User, : Ri



$$R_i = \langle (i), (e_1, e_2, \dots, e_n), (a_1, a_2, \dots, a_m) \rangle$$

where

$$E_i = (e_1, e_2, \dots, e_n)$$

Event Stream for User i

$$A_i = (a_1, a_2, \dots, a_m)$$

Set of measured values for the session of User i

$$R_{1} = \langle (1), (e_{1}, e_{2}, \dots, e_{n}), (a_{1}, a_{2}, \dots, a_{n}) \rangle$$

$$R_{2} = \langle (2), (e_{1}, e_{2}, \dots, e_{n}), (a_{1}, a_{2}, \dots, a_{n}) \rangle$$

$$R_2 = \langle (2), (e_1, e_2, \dots, e_n), (a_1, a_2, \dots, a_m) \rangle$$

$$R_n = \langle (n), (e_1, e_2, \dots, e_n), (a_1, a_2, \dots, a_n) \rangle$$

PHASE II: Performance Parameters

Determine and calculate the usability related numerical performance parameters from the session log file

❖ For any system/product designers collaboratively determine potential indicators that will apply best to their purposes

Examples from HCI literature:

- •task completion time
- repetitions
- cancellations and undo's
- the frequency and patterns in use of help
- time spent in a window
- ❖ Selected Indicators are calculated for each user

OUTPUT OF PHASE II

	INDICATORS			
USERS (<i>U_i</i>)	I_1	I_2	•••	I_{m}
${U}_{\scriptscriptstyle 1}$	i_{11}	i_{12}		$oldsymbol{i}_{1m}$
${U}_2$	i_{21}	i_{22}	•••	i_{2m}
${U}_{\scriptscriptstyle n}$	$oldsymbol{i}_{n1}$	i_{n2}		\dot{t}_{nm}

<u>PHASE III</u>: Clustering Subjects with respect to the results

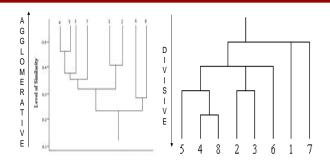
Objective: To find clusters that will represent the sample space in the least costly way

Clustering in Data Mining

Partitional Clustering
Partition the data set into
k clusters

- •K-Means
- •K-Medoids

Hierarchical Clustering Produce a nested sequence set of partitions



PHASE III: Clustering Subjects with respect to the results

Objective: To find clusters that will represent the sample space in the least costly way

PHASE IV : Approach I

Extracting recurring paths in each cluster and comparing these paths with the designer data and/or among user clusters.

Apriori Algorithms (Agrawal and Srikant, 1995): Mining traversal patterns in a cluster & choosing the frequent patterns

Log files in Cluster k

$$R_i = \langle (i), (e_1, e_2, \dots, e_n) \rangle$$

$$R_{i+1} = \langle (i+1), (e_1, e_2, \dots, e_n) \rangle$$

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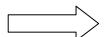
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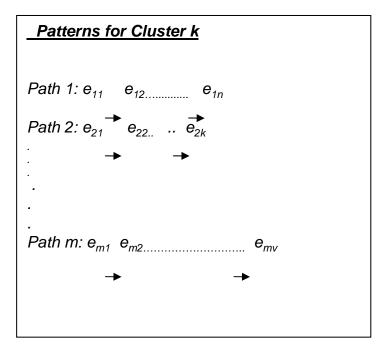
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$$R_{i+1} = \langle (i+1), (e_1, e_2, \dots, e_n) \rangle$$

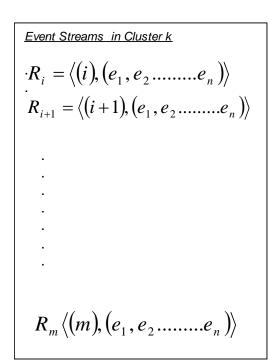


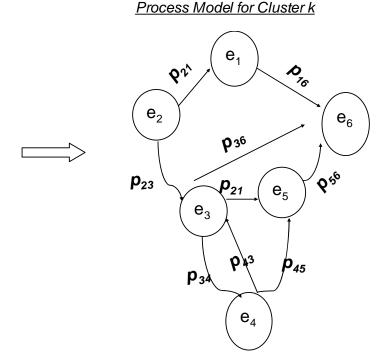


PHASE IV : Approach II

Building a process model for each cluster from execution logs

Probabilistic Methods



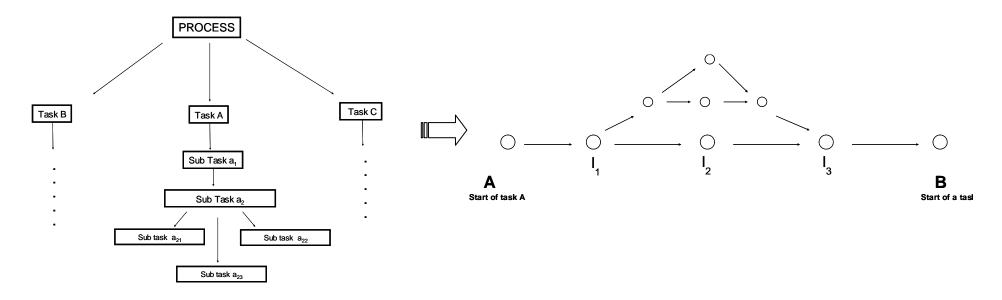


Process Model for Cluster k

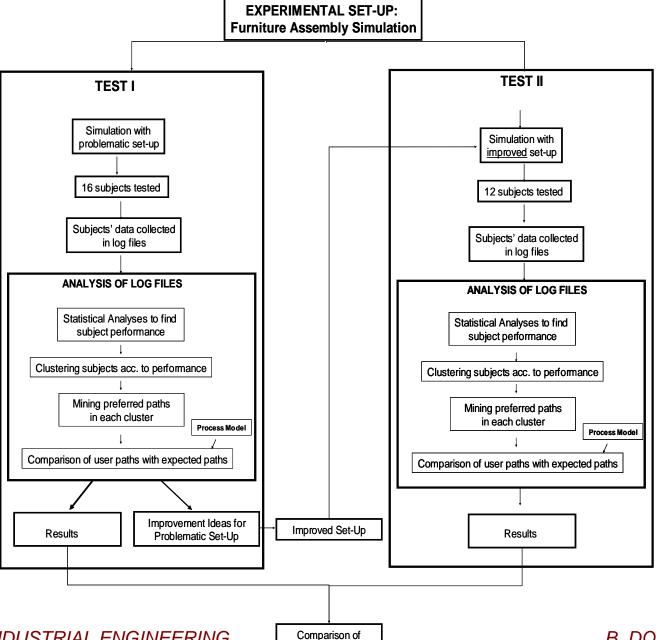
PHASE IV : Approach III Sequence Comparison

Objective: Detect paths that diverge from target sequences Detect points at which divergence starts and ends

PROCESS MODEL EXPECTED PATHS PATH COMPARISON



EXPERIMENT



Results

EXPERIMENT

TEST ENVIRONMENT

Simulation of assembly process of newly purchased home furniture

- 28 subjects
 - -27 Concordia University students,1 university graduate
 - -No financial compensation
- In Concordia University graduate laboratories
- Time spent is 15 minutes

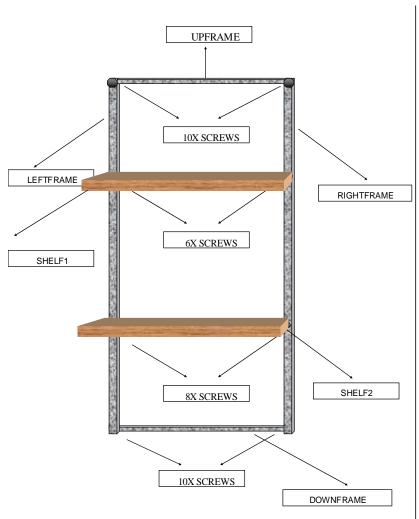
ITEM TO BE ASSEMBLED

Wall mounted shelving unit that consists of :

- Side frames
- Up & down frames
- Shelves
- Screws of different types

EXPERIMENT

ASSEMBLY INSTRUCTIONS FOR THE WALL MOUNTED SHELVING UNIT

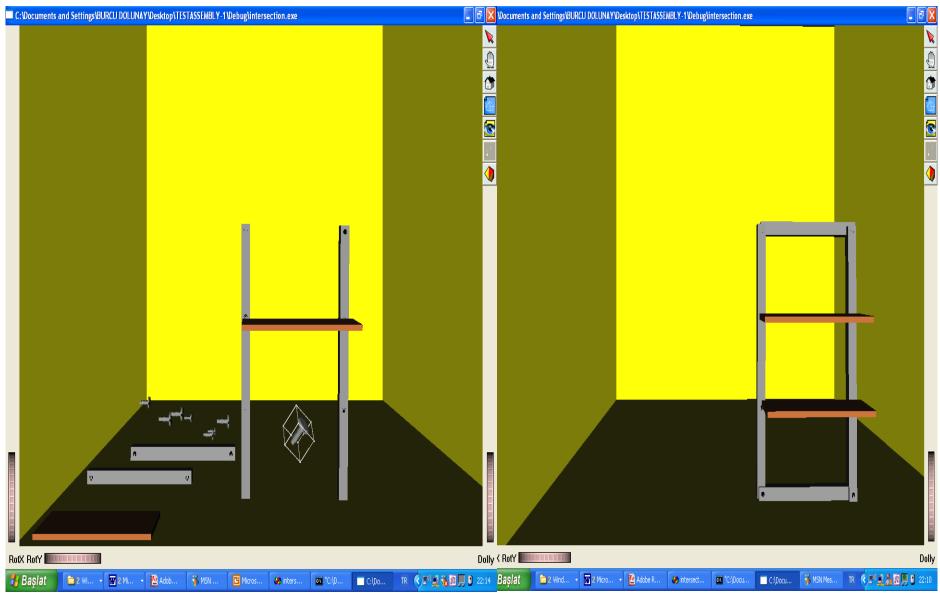


- 1. Assemble left frame.
- 2. Pick a 10x screw and place to the top hole of the right frame.
- 3. Pick the second 10x screw and place to the top hole of left frame.
- 4.Pick a frame and assemble to the top holes on the left and right frames.
- 5. Pick a 10x screw and place to the bottom hole on the right frame.
 - 6. Pick the last 10x screw and place to the bottom hole.
- 7. Pick the second frame and assemble to the down holes on the left and right frames.
- 8. Pick a 6x screw and place on the upper middle hole of right frame.
- 9. Pick a 6x screw and place on the upper middle hole of left frame.
 - 10. Pick a shelf and assemble on the upper holes.
 - 11. Pick an 8x screw and place on the lower hole of right frame.
 - 12. Pick an 8x screw and place on the lower hole of left frame.
 - 13. Pick the other shelf and assemble on the lower holes.

TEST ENVIRONMENT



TEST ENVIRONMENT



DURING

COMPLETED

MECHANICAL & INDUSTRIAL ENGINEERING

B. DOLUNAY,2006

DATA ANALYSIS

INDICATORS TO BE COLLECTED

Task Completion Times & Repetitions & Cancellations

CLUSTERING

Correlation Analysis : Pearson Correlation Coefficient

Repetitions & Cancellations: 0.127501763

Time & Repetitions: 0.262578038
Time & Cancellations: 0.210673528

No Evident Linear Relationship

Clustering on 3-dimensions: 3 Clusters (CL1: 11, CL2:3, CL3:2)

Data Standardization (Kaufman et al., 1990)

- K-means Clustering Algorithm
 - ✓ Simple, effective
 - Outlier sensitivity
 - One data point in one cluster

DATA ANALYSIS

Approach I - Extracting recurring paths in each cluster and comparing these paths with the designer data and/or among user clusters.

Maximal Forward Sequences Algorithm (Chen et al., 1994)

- Find maximal forward sequences for each user
 Eliminate repetitions, cancellations
 Can not be a subsequence of any other path
- Collect the logs of a cluster in the same file
- Scan the file for repeating patterns Similarity coefficient

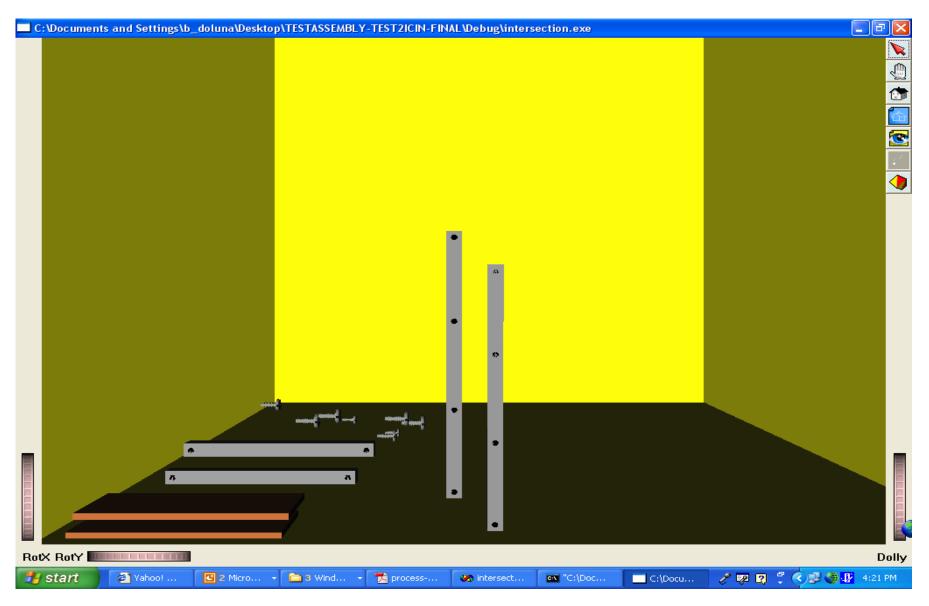
Approach II - Sequence Comparison

- Obtain sub-paths from process model
- Compare with subject paths

EXPERIMENT I

- > SIMULATION WITH PROBLEMATIC SCREWS
 - **▶16 SUBJECTS**
- **COMMON PRACTICE IN FURNITURE STORES**
 - FACED IN DAILY LIFE BY NOVICE PEOPLE

EXPERIMENT I



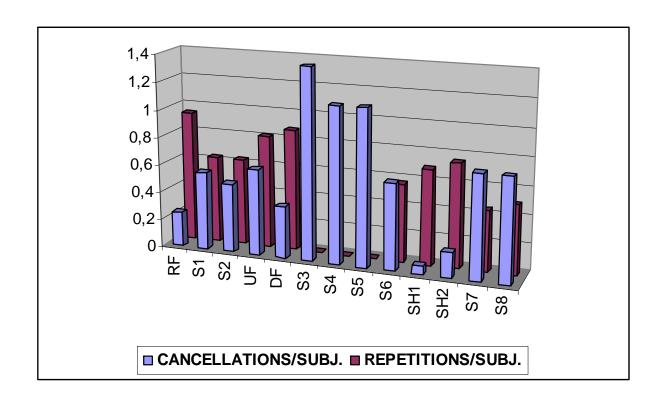
EXPERIMENT RESULTS

TEST I: Statistical Results

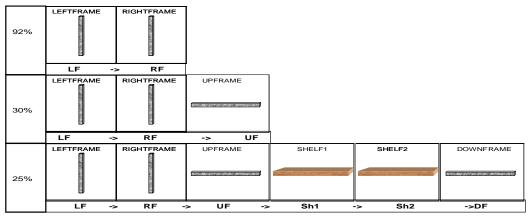
•Mean task completion time: 9.522 minutes,

•Mean number of repetitions: 3.9

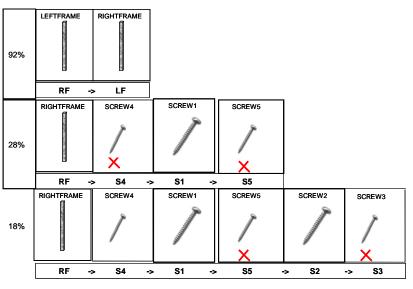
•Mean number of cancellations : 4.67

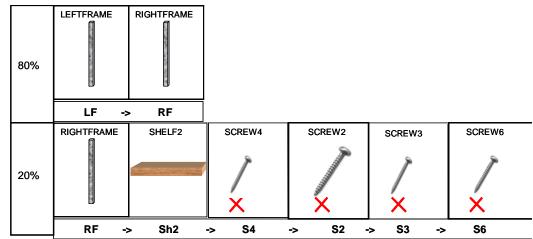


TEST I : Path Analysis



Paths from Cluster I



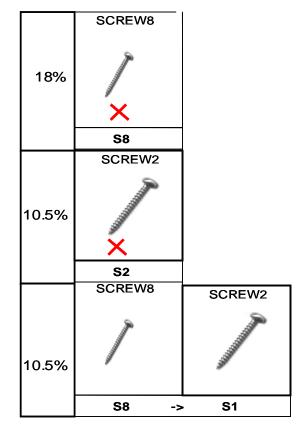


Paths from Cluster III

Paths from Cluster II

TEST I: Path Analysis - Comparison with Expected

- ❖ Number of violating paths is 57
- ❖ Mean deviation: 3.56 per user
- ❖ Mean path length is 3.14
 - shortest pattern consists of one event,
 - longest pattern consists of 11 events
- Long paths were not frequent
- ❖ %12.5 started after the
 "assembly of down frame
- ❖ 14% turned back to normal with "picking screw1" and "picking screw2"



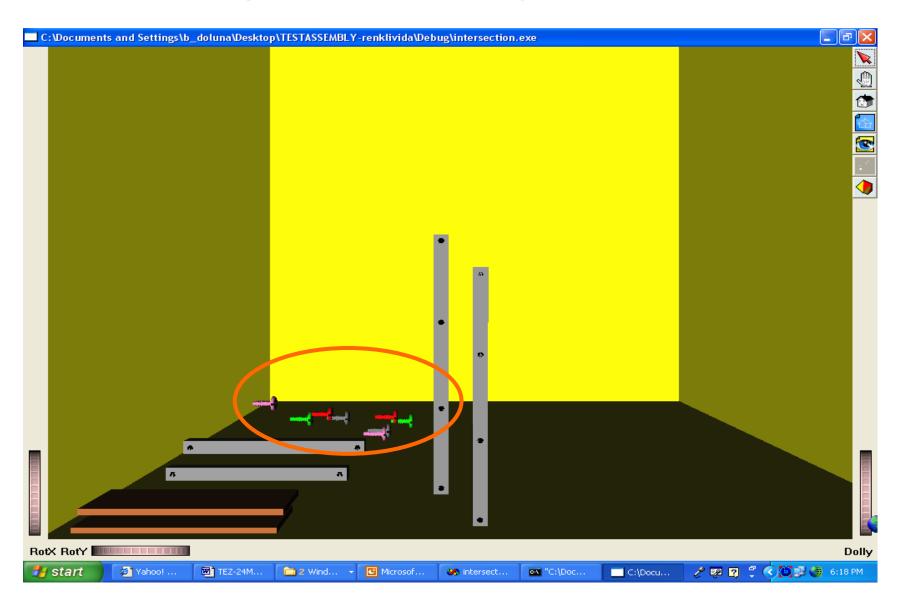
Violating sub paths

EXPERIMENT II

> SIMULATION WITH <u>DIFFERENT</u> COLOR SCREWS

▶12 SUBJECTS

TEST ENVIRONMENT

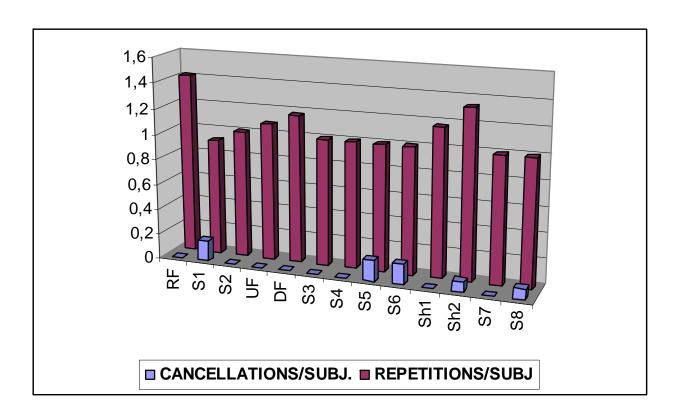


TEST II: Statistical Results

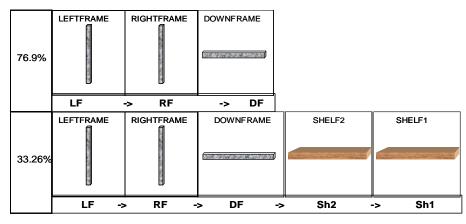
•Mean task completion time: 2.397 minutes,

•Mean number of repetitions : 2.25

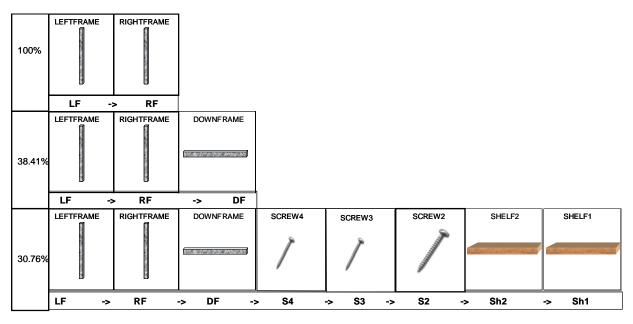
•Mean number of cancellations : 0.667



TEST II : Path Analysis



Paths from Cluster I



Paths from Cluster III

TEST II : Path Analysis - Comparison with Expected

- ❖ Number of violating paths was is 7
- ❖ Mean deviation: 0.58 tasks per user
- ❖ Mean path length is 1.14
 - shortest pattern consists of one event,
 - longest pattern consists of two events
- Only one 2-event path

COMPARISON OF RESULTS

- ➤ Mean assembly completion time decreased by 28.57% (p<0.05)
- ➤ Mean number of cancellations decreased by 43.2% (p<0.025)
- > Decrease in the number of repetitions is not significant
- > Total number of deviating paths

57 in the first test vs. 7 in the second test



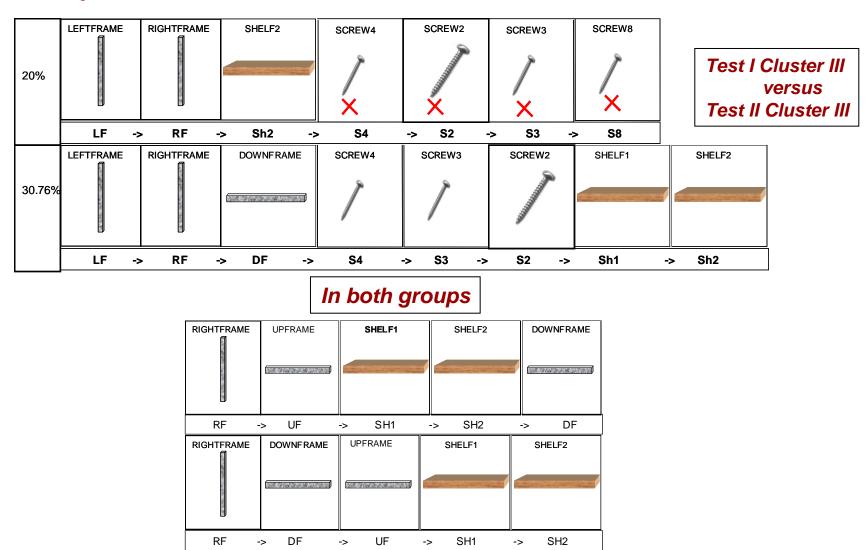


3.56deviations per subject

- 0.58 deviations per subject
- ➤ The mean length of deviation: 3.14 in the first test vs. 1.14 in the second test

COMPARISON OF RESULTS

Path Analysis



POTENTIAL APPLICATIONS OF THIS WORK

IN THE AREA OF A NEW PRODUCT DEVELOPMENT

- Provides valuable insight about users' experience with product, enables more efficient design changes
- Enables testing products in early stages of product life

FOR EXISTING SYSTEMS/PRODUCTS: AFTER SALES SUPPORT <u>Training:</u>

- Seeing user patterns means better insight about the weak points
- Increased efficiency in the training programs
- Increased user satisfaction

<u>Maintenance:</u>

For complex systems on a wide geographical region:

- Ability to trace the processes followed by different branches for maintenance of systems,
- Detect deviations from the expected maintenance process
- Ability to provide remote support without having to send people to the actual place

CONLUSION & FUTURE WORK

The methodology is applicable whenever there is a need to understand if the product is functioning as expected on user's side

ADVANTAGES:

- * Automated data collection and analysis on large sample spaces
- ❖ No location and time constraints

FUTURE WORK:

- ❖ Collecting all tools and proposed data analysis methodology in a user friendly interface
- Enabling different choices in the interface at each phase
- ❖ Integration of a visualization aid for data presentation after analysis
- Analysis of concurrent activities, activities that happen at the same time

THANK YOU...

QUESTIONS?