RESISTING RELIABILITY DEGRADATION THROUGH PROACTIVE RECONFIGURATION

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Definitions

RESIST

- **RE**silient SItuated SofTware system
- "A framework for mission-critical systems"
- Situated Systems (SS)
 - Embedded
 - Mobile
 - Pervasive
 - Ex. Mobile devices, robots
- Mission Critical
 - Ex. Emergency response, disaster recovery

Core Problem

- Mission critical systems require high reliability
 - Situated systems are inherently unreliable
 - External factors play a huge role in this
- The best configuration for a system is known only at runtime
 - Need to update configuration to improve reliability
- □ How do we design such a system?

What does **RESIST** do?

Self-healing / Self-optimizing



What assumptions does RESIST make?

- Errors are assumed to be between components
 - Errors internal to the component are not handled by this error model
- Configurations may have replicas of components
- Replicas of different components fail independently

How is **RESIST** different?

- Optimizes proactively
 - Uses predictive models to optimize ahead
 - Focuses on where system is expected to be
 - Different from other systems that focus on current state
 - Note: Can only focus on near-future
- Considers external factors (Context)
- Other related work not appropriate
 - Expects apriori knowledge of reliability
 - Do not consider context

How does **RESIST** work?

- Determine optimal configuration of components for SS
 Optimal = most reliable
 - Calculate individual component reliabilities
 - Calculate total system reliability
 - This is based on individual component reliabilities
 - Consider architectural factors
 - Redundant components
 - Assignment of components to processes

Scenario

Emergency response

- Firefighters
- Central dispatcher
- Robots
 - Components
 - Sensors
 - Actuators
 - Controllers



Uses Hidden Markov Models (HMMs)

Normal Markov Model



Normal Markov Model

Can predict next state based purely on current state



Hidden Markov Models (HMMs)

HMMs extend this idea by adding hidden states



Set of observations

$$O = \{O_1, O_2, \ldots, O_N\}$$

Observation probability matrix

 $E = \{e_{ik}\}$ This represents the probability of observing an event in a particular state



Real State Transitions



Real State Transitions



Training the HMM

States are known

Ex. Monitoring, moving

Need to determine transition probability matrix

- Can learn this from monitoring data
 - This gives us observations
- Train using sample data
 - Baum-Welch algorithm
 - Method for finding the hidden parameters in an HMM
 - Uses expectation-maximization

Predictive Calculations

Calculating reliability at runtime before failure

- Involves the use of "context"
 - These are events or processes outside of the system that affect it
 - Must be included in calculations for situated systems

Introduce a new set of parameters:

Set of contextual parameters

 $C = \{C_1, C_2, \ldots, C_N\}$

Using Context in Reliability Calculations

□
$$a'_{kj} = u(a_{kj}, \Delta C_n)$$

□ a_{kj} - transition probability

u – a function that based on context

Encapsulates the effect that C_n has on $a_{k\dot{1}}$

Calculating Total System Reliability

Based on individual component reliability

$$R = (-1)^{k+1} R_k \frac{|E|}{|I-M|}$$

k = Number of states

- $\square R_k =$ Reliability of exit state
- $\square M = Matrix of size k x k$
- \square |I-M| = Determinant of M
- E |E| = Determinant of everything but the first column and row of |I-M|

Considering Architectural Factors



Considering Architectural Factors



More efficient architecture

More reliable architecture

Finding Optimal Configuration

Reliability is the goal
In practice, other factors may influence calculation $C^* = argmax_{(C)} \sum_{\forall q \in QualityObjectives} U_q(C)$ Subject to $R(C) \ge \delta, \delta \in \mathbb{R}, 0 < \delta \le 1$

U_q = Utility function
 Can take on any format

Finding Optimal Configuration

- Configurations have constraints
 - Must be assigned to at least one process
 - Can have a bounded number of replicas
 - Cannot share a process and have a replica
 - Components and replicas should be on separate processes

Experimental Results

- Robot example from earlier
- Context probability of hitting an obstacle
 - Bump probability (BP)
- Controller failure is examined with respect to different BP
 - This is because the transition from one state to another can fail with a certain probability

Experimental Results

Observed and predicted reliability
 Shows accuracy of predictive model

Reliability degrades with context
 Increased BP = lower reliability



Experimental Results

- Real robotic results
- RESIST sees a increase in BP
 - This is predicated to result in a drop in reliability
 - Before this degradation in reliability, RESIST
 - "adapts the system to maintain its reliability above 97%. As a result, the Navigator is replicated and the Controller is redeployed to a separate process."



Conclusion

- Overall, the paper covers a lot of ground
- Offers an interesting, predictive approach
- Questions
 - What other machine learning techniques can be used to aid prediction?
 - Does the system's accuracy improve with more data / examples?

References

- Deshan Cooray, Sam Malek, Roshanak Roshandel, David Kilgore, RESISTing reliability degradation through proactive reconfiguration, Proceedings of the IEEE/ACM international conference on Automated software engineering, September 20-24, 2010, Antwerp, Belgium
- http://en.wikipedia.org/wiki/Baum-Welch_algorithm