Dynamic Influence Nets: An Extension of Timed Influence Nets for Modeling Dynamic Uncertain Situations

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June 14, 2005
10th International CCRTS, McLean VA
Outline of the Presentation

• Technical Background
  – Influence Nets
  – Timed Influence Nets

• Limitations of Timed Influence Nets
  – Different sequences of Actions have no impact on the final probability of achieving a desired effect
  – Influences are assumed to be time-invariant

• Proposed Methodology
  – Adding memory to the nodes in a TIN
  – Modeling of time-varying influences

• Dynamic Influence Nets

• Conclusions
Influence Nets

- A set of random variables that makes up the nodes of an IN. All the variables in the IN have binary states.
- A set of directed links that connect pairs of nodes.
- Each link has associated with it a pair of parameters that shows the causal strength of the link (usually denoted as \( h \) and \( g \) values).

\[ h \] is Influence of \( A \) on \( B \): Analogous to \( P(B \mid A) \)
\[ g \] is Influence of \( \neg A \) on \( B \): Analogous to \( P(B \mid \neg A) \)
Probability Propagation in Influence Nets

\[ P(A) = P(A|\neg B, \neg E)P(\neg B)P(\neg E) + P(A|\neg B, E)P(\neg B)P(E) + P(A|B, \neg E)P(B)P(\neg E) + P(A|B, E)P(B)P(E) \]
\[ = 0.005 \times 0.95 \times 0.99 + 0.95 \times 0.95 \times 0.01 + 0.95 \times 0.05 \times 0.99 + 0.99 \times 0.05 \times 0.01 \]
\[ = 0.06 \]

\[ P(D) = P(D|\neg E, \neg A)P(\neg E)P(\neg A) + P(D|\neg E, A)P(\neg E)P(A) + P(D|E, \neg A)P(E)P(\neg A) + P(D|E, A)P(E)P(A) \]
\[ = 0.05 \times 0.99 \times 0.94 + 0.95 \times 0.99 \times 0.06 + 0.001 \times 0.01 \times 0.94 + 0.05 \times 0.01 \times 0.06 \]
\[ = 0.11 \]
The specification of a TIN require the following additional parameters besides the one required for by an ordinary IN:

- A time delay is associated with each arc.
- A time delay is associated with each node.
- Each actionable event is assigned time stamp(s) at which the decision(s) regarding the state of that action is(are) made.
Problem Statement

Given
- A Dynamic Uncertain Situation
- A Set of Desired Effects
- A Set of Actionable Events

- How to capture certain dynamic situations
  - Modeling of time-varying influences
    - Strength of the influence changes over time
    - Influence vanishes over time
  - Modeling of memory to help in identifying
    - Impact of repetitive actions on the desired effects
    - Impact of different sequence of actions on the desired effect
Current implementation of TINs models time-invariant influences. A scheme is proposed for modeling time-varying influences. A list of influences along with their time of effect is specified for each arc in a TIN. The proposed scheme can be used to model time-dependent structural changes in a TIN.

Influence of A on C when information at A is t time units old:
- Strong: $2 \leq t < 4$
- Moderate: $4 \leq t \leq 6$
- Low: $t > 6$

Influence of B on C when information at B is t time units old:
- Strong: $1 \leq t < 3$
- Low: $t > 3$
C is updated at time: 6, 8, 11

At time 6: P(A) @ 4 is used, while P(B) @ 0 is used

- Information coming from A is 2 time units old
- Information coming from B is 6 time units old
  - C has strong influence of A and low influence of B at time 6

At time 8: P(A) @ 4 is used, while P(B) @ 7 is used

- Information coming from A is 4 time units old
- Information coming from B is 1 time units old
  - C has moderate influence of A and strong influence of B at time 8
Non-Stationary Conditional Probabilities

Influence of A on C when information at A is t time units old
- Strong: $2 \leq t < 4$
- Moderate: $4 \leq t \leq 6$
- Low: $t > 6$

Influence of B on C when information at B is t time units old
- Strong: $1 \leq t < 3$
- Low: $t > 3$

<table>
<thead>
<tr>
<th>Parents Combination</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6</td>
</tr>
<tr>
<td>$P(C</td>
<td>\neg A, \neg B)$</td>
</tr>
<tr>
<td>$P(C</td>
<td>A, B)$</td>
</tr>
<tr>
<td>$P(C</td>
<td>A, \neg B)$</td>
</tr>
<tr>
<td>$P(C</td>
<td>A, B)$</td>
</tr>
</tbody>
</table>

$P(A) = 0.05 @ 0$
$= 1.0 @ 4$

$P(B) = 0.1 @ 0$
$= 0.6 @ 7$
$= 1.0 @ 10$
Given

- A Dynamic Uncertain Situation
- A Set of Desired Effects
- A Set of Actionable Events
  - How to capture certain dynamic situations
    - Modeling of time-varying influences
      - Strength of the influence changes over time
      - Influence vanishes over time
    - Modeling of memory to help in identifying
      - Impact of repetitive actions on the desired effects
      - Impact of different sequence of actions on the desired effect
Adding Memory to the Nodes in a TIN

• Current implementation of TINs assume that the nodes are memoryless
  – The impact of different sequences of actions is not captured.

• An approach is proposed that adds memory to the nodes in a TIN
  – A self-loop is added to each node whose current state is dependent on its previous state.

A @ 10, B @ 12

Same Final Probability

A @ 10, B @ 12

B @ 10, A @ 12
Adding Memory to the Nodes in a TIN (Cont’d)

B @ 10, A @ 12

(0.90, -0.90) Strong Memory

(0.33, -0.33) Weak Memory
Dynamic Influence Nets

- Timed Influence Nets with
  - Time-varying influences
  - Memory represented by a self-loop

Influence of A on C when information at A is t time units old
Strong: 2 \leq t < 4
Moderate: 4 \leq t < 6
Low: t > 6

Influence of B on C when information at B is t time units old
Strong: 1 \leq t < 3
Low: t > 3

P(A) = 0.05 \text{ @ 0 } 
= 1.0 \text{ @ 4 }

P(B) = 0.1 \text{ @ 0 } 
= 0.6 \text{ @ 7 } 
= 1.0 \text{ @ 10 }
Summary

• Extended the knowledge elicitation interface of TINs so that they can capture time-varying cause-effect relationship
  – Instead of providing a single-valued strength of cause-effect relationship, a system modeler can specify multi-valued strengths of cause-effect relationship along with their time of effectiveness
• Added a mechanism to incorporate memory in a TIN to capture the impact of repetitive actions and different sequence of actions on the desired effect
  – A self-loop is added to a node that captures memory of the node
  – The strength of the self-loop specify whether the modeled memory is weak or strong
• Together these two features capture the impact of repetitive actions
Questions?