Exploiting Petri-net Structure for Activity Classification and User Instruction within an Industrial Setting

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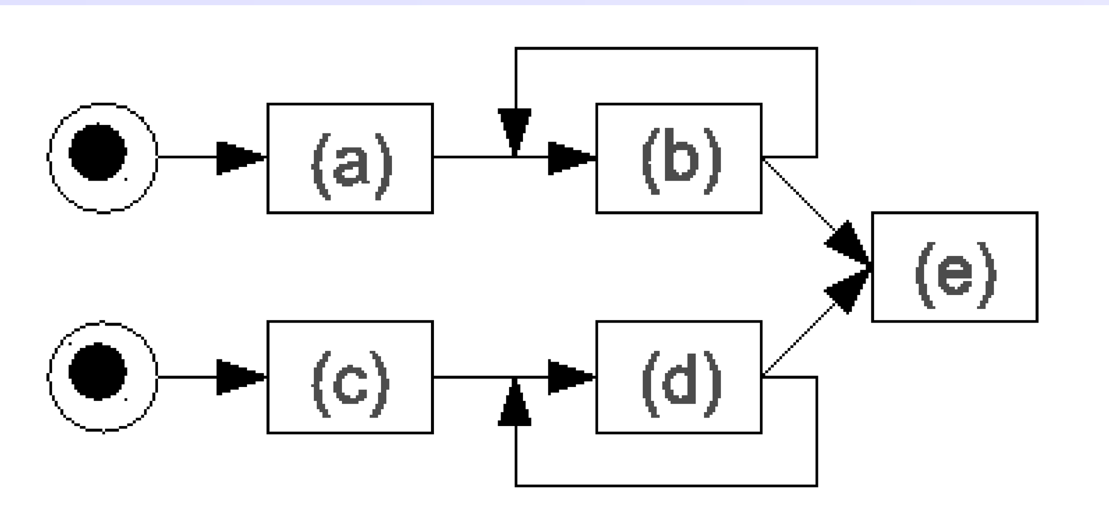
SEVENTH FRAMEWORK PROGRAMME

Abstract

Live workflow monitoring and the resulting user interaction in industrial settings faces a number of challenges. This paper attempts to address these problems by inducing a structural workflow model from multiple expert demonstrations. When interacting with a naive user, this workflow is combined with spatial and temporal information, under a Bayesian framework, to give appropriate feedback and instruction. Structural information is captured by translating a Markov chain of actions into a simple place/transition Petri-net. This novel petri-net structure maintains a continuous record of the current workbench configuration and allows multiple sub-sequences to be monitored without resorting to second order processes. This allows the user to switch between multiple sub-tasks, while still receiving informative feedback from the system.

Motivation

In 'state-of-the-art' HMM/CFG approaches, detection accuracy is often dependent upon the final re-estimation of the Viterbi path, far too late for live activity recognition and user instruction. Additionally, CFG structures are incapable of capturing certain real workflow features such as limited depth recursion and temporally independent subtasks, while hand crafted workflows can fail to capture expert behaviour [1]. Moreover, Petri-net formalisms can be easily translated into human readable and editable workflow formats in the form of a graph of states, transitions, arcs and markers.



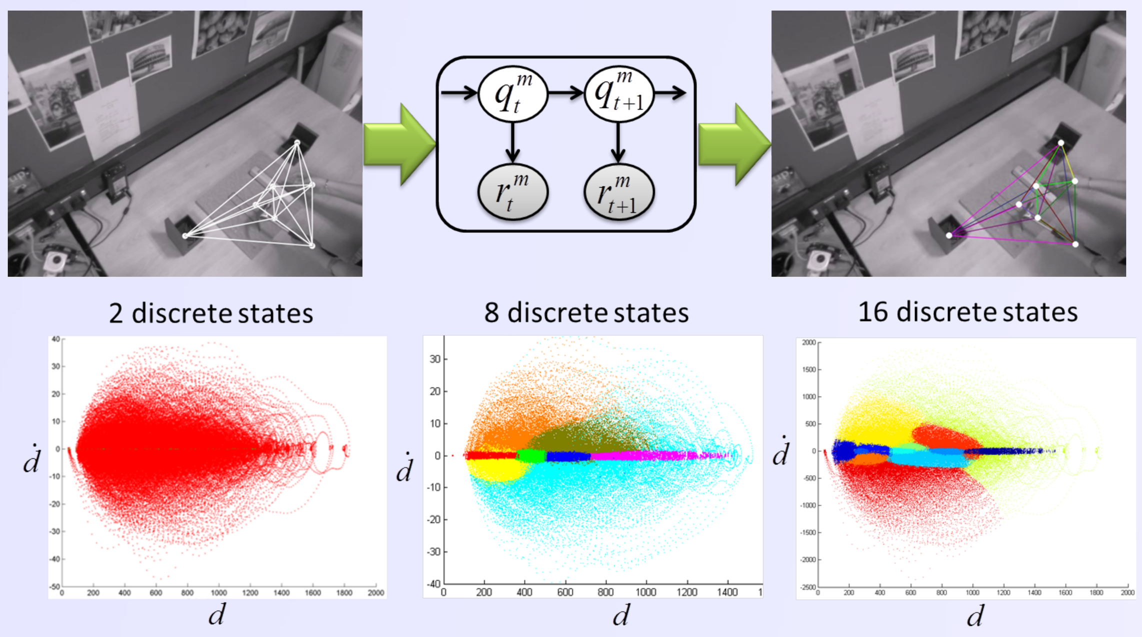
A simplified representation of an induced Petri-net, showing parallel sequences and recursive processes.

In the proposed induced Petri-net workflow model, we address the following HMM/CFG shortcomings.

1. Maintains 'on-line' classification accuracy from partial information – enabling the accurate instruction of a live user.
2. Exploits a marker based transition network to capture the structural properties of the workbench.
3. Provides structural classification constraints that can be translated into real workflows.
4. Successfully trains over relatively sparse annotated data sets.
5. Induces and exploit workflows from example activity sequences – capturing what is done not what 'should' be done.

Relational Feature Quantisation

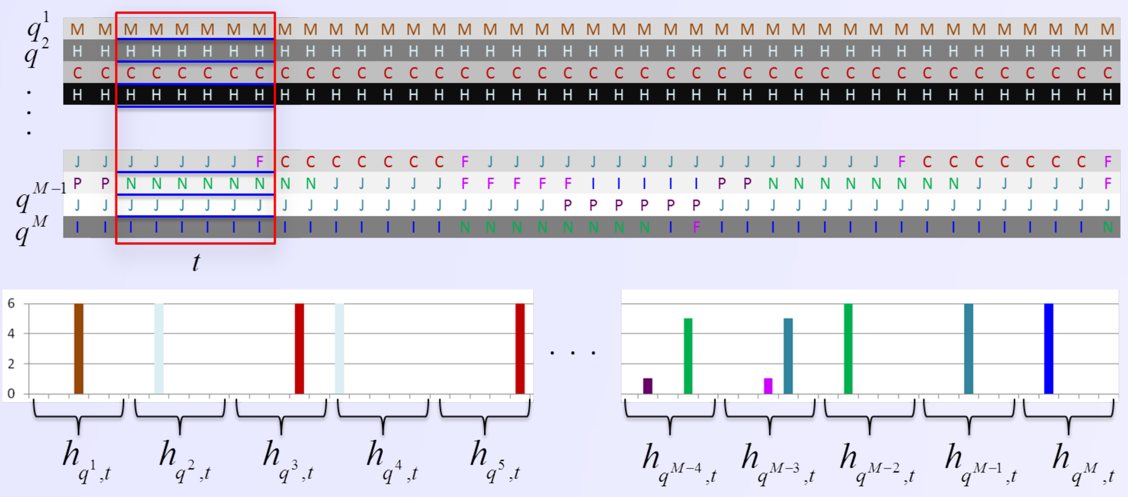
At each time step t, the relation between a pair of objects is represented as a real valued vector, which is composed of the separation and the first derivative of separation with respect to time *i.e.* $\boldsymbol{r}_t^{i,j} = (d_t^{i,j}, \dot{d}_t^{i,j}) \in \Re^2$, for $\forall i < j$ [2].



Quantisation of pairwise relations between key objects in a workbench for a varying number of latent HMM states.

Naive Bayes Model Formation

At each timestep, a Histogram of Pairwise Relationships (HoPR), $\boldsymbol{h}_t = (h_{q^1}, \cdots, h_{q^M})$ is computed over a sliding window of size w.



Histogram of pairwise relations (HoPR) over a sliding window on quantised pairwise relations between all key objects.

A workflow instance e is defined as a tuple (H_e, g), where $H_e = h_1 \cdots h_t$, representing a series of HoPR, and g assigns an action to each HoPR. Activity $a_i \in A$ occurs in e, if $\exists$: $h_j \in H_e$ with $g(h_j) = a_i$. Using a SVM, the model first computes the probability distribution $P(a_t^i|h_t, \Delta)$ over a_i, where $|\Delta| = |A|$, and f_Δ: $\delta_i \in \Delta \rightarrow a_i \in A$.

Absolute temporal prior of atomic event a_2 in the workflow instance e_1.

Absolute temporal prior of atomic event a_9 in the workflow instance e_1.

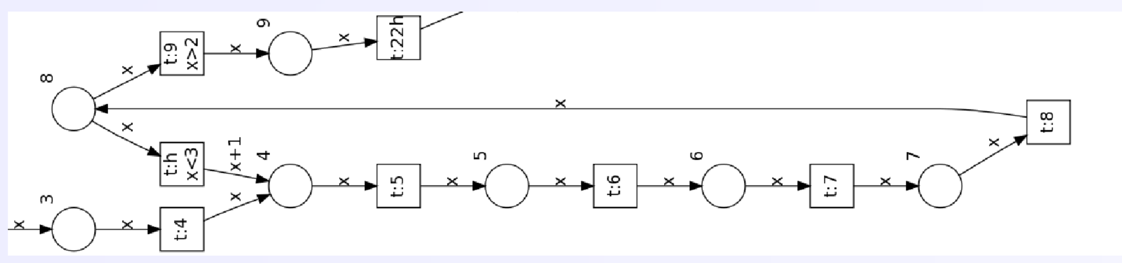
In the second, the model computes the absolute temporal prior $P(a_t^i|t, \Omega) = \frac{\omega(a^i,t)}{\sum_{j=1}^{|A|}\omega(a^j,t)}$ over atomic action a_i by using a Gaussian model $\omega_i \in \Omega$, where $\omega(a^i,t) = \frac{1}{\sqrt{2\pi a_{i,\sigma}^2}} e^{-\frac{(t-a_{i,\mu})^2}{2a_{i,\sigma}^2}}$.

Finally, a transition probability matrix $P(a_t^i|\theta, S_{t-1}) = \sum_{j=1}^{|S^{t-1}|} P(s_t^i|s_{t-1}^j, d_\gamma^{i,j})P(s_{t-1}^j)$ is calculated according to the induced Petri-net structure to capture the structural transitions of the induced workflow [3]. $s_{t-1}^j \in S_{t-1}$ and $d_\gamma^{i,j}$ equals the minimum number of transitions between s_t^i and s_{t-1}^j.

Activity Recognition

At each timestep, the most likely action is computed using naive Bayes *i.e.* $a_{MAP} = \arg\max_{a_t}\{P(a_t|h_t, \Delta)P(a_t|t, \Omega)P(a_t|\theta, S_{t-1})\}$

Similarly, given the current believed state of the Petri-net, the next likely action $a_{MAP}^{t+1} = \arg\max_{a_{t+1}, a_{t+1} \neq a_t} \{P(a_{t+1}|\theta, S_t)\}$.



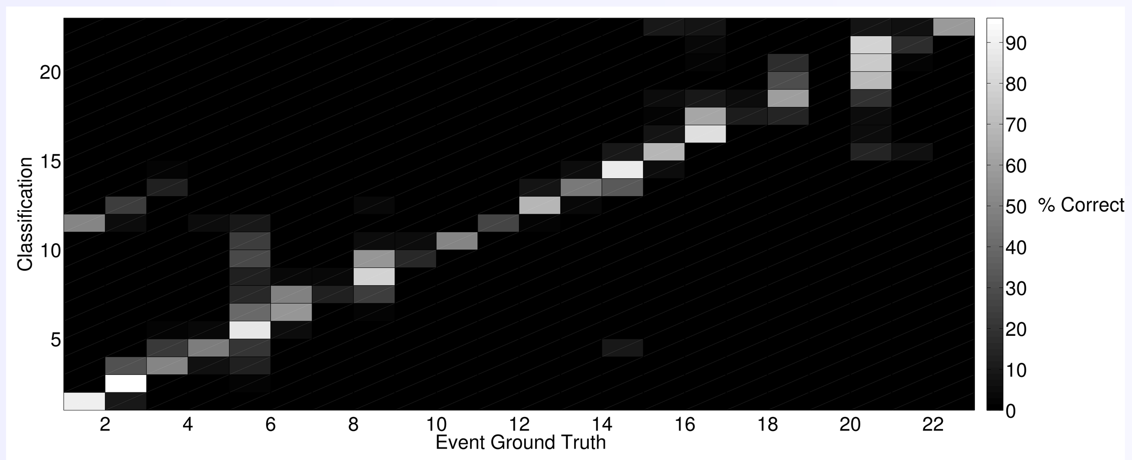
A detailed view of component (d) by transitioning from a place/transition to a Petri-net we can limit the number of recursive transitions within the workflow.

Evaluations and Discussion

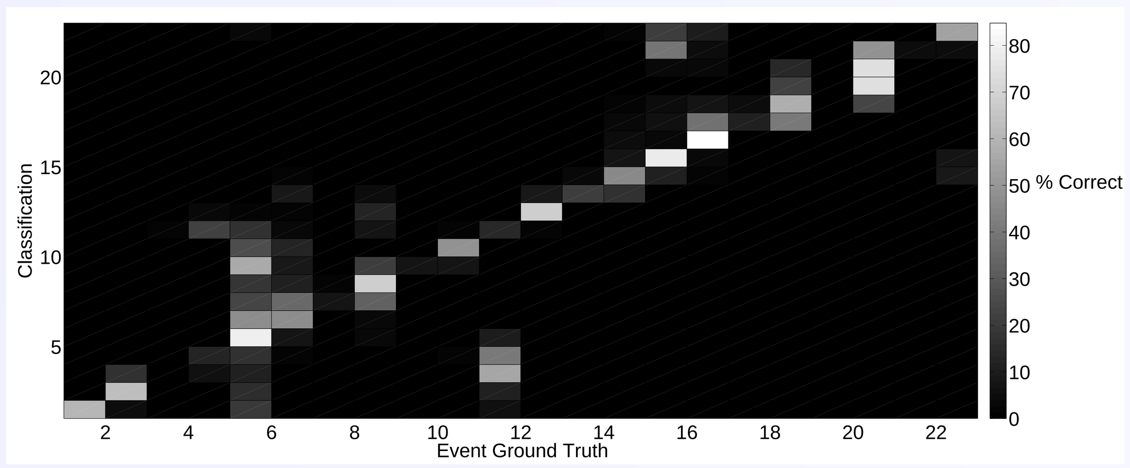
The dataset consists of two tasks performed eight times by two people on the same workbench. The workbench consists of 9 key objects, each of which is tracked by a VICON marker.

Model	Accuracy %
On-line-HMM	12.2
pLSA	36.8
HoPR-SVM	62.5
HoPR-NB	70.1

A state-of-the-art HMM approach performed well for off-line classification (77.2%). However, the performance deteriorates significantly for on-line (12.2%). HoPR-NB outperforms the state-of-the-art, the unconstrained HoPR-SVM model for leave-one-out classification accuracy.



Confusion matrix for the HoPR Naive Bayes model.



Confusion matrix for the HoPR SVM model.

The classification results reveals that due to the structural constraints of the Petri-net, the majority of classification errors occur at the transition points from one action to the next.

Acknowledgment

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References

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