

## ***Paper review***

### ***Activity Recognition with Finite State Machine***

This paper is mainly concerned about a general approach to activity recognition using Finite State Machine (**FMS**). It uses some training data set specified as propositions that have truth values. For the classification of fluent which varies in the intervals of time it is not necessary to use whole data for classification and generalisation of behaviour of activity as all the component of activity might be repeating during that interval so we reduce them to single characteristic in this way generate compressed bit array (CBA) from given data set of propositions propositional multivariate time series (PMTS). Here we are trying to learn generalisation of instances of activities for that we have to establish relationships between fluent used in instances of activity which can be done using Allen relations. The relationship is established in the form of qualitative sequence which can be obtained using by first normalizing [Winarko and Roddick, 2007] and sorting based on first finishing time than using the algorithm Make-Sequence as described in paper. By using interaction-window size of qualitative sequence can be shortened. Signatures are formed from qualitative sequence of activity which is ordered sequence of weighted Allen relations. Signatures are updated using dynamic programming with Needleman-Wunsch global sequence alignment algorithm<sup>1</sup>. Only Insert or match is allowed for sequence alignment to prevent data loss and data is pruned after a fixed number of training instances based on weight of element so that size of signature did not get higher. Now the main part is to decide the less important fluent and which is done using weights of each relation respective to a fluent if no one exceeds a threshold then it will be considered as less important and can be removed from formation FSM using CBAs. Now FSMs with respect to every instance are merged and final state of those instances is made accepting state in final FSM and this FSM is used as *recogniser*. Now we will have multiple trained FSM's one for each activity. "Now we count true positive(*tp*) for FSM<sub>*i*</sub> recognises instance of activity *i*, False positive(*fp*) for FSM<sub>*i*</sub> recognizes an instance of activity *j*, true negative (*tn*) for FSM<sub>*i*</sub> accept an instance of activity *j*, false negative (*fn*) FSM<sub>*i*</sub> rejects an instance of activity *i*. Recall is defined  **$asrec=tp/(tp+fn)$**  and precision as  **$asprec = tp/(tp+fp)$** . We report the F1measure:  **$2(prec \times rec)/(prec+rec)$** ." [Kerr et al., 2011]. Data used for analysis is of 3 different categories first Wubble World 3D (ww3d), [Kerr et al., 2008] , second Wubble World 2D (ww2d) and

third from individual's handwriting [Kerr, 2010]. And recognition of previously unseen test cases is evaluated based on F1 score. And according to the characteristic of data it is observed that as performance increases quickly with increase in training data. In case if one activity is observed to be the component of other activity than performance of component part would be lower as it would be accepted false positive (fp) for other activity and this would lower the performance. Generally the research on temporal patterns in interval time series is based on extracting classification or patterns based on threshold frequency. Previously temporal patterns were described by Allen relations and an Apriori -like algorithm [Agrawal and Srikant, 1994] But this paper introduced a new way represent them as Finite State Machine(FSM). "Overall, the recognizers perform with F1 scores at or above 0.7 across all three datasets." [Kerr et al., 2011]

## References:

[Kerr et al., 2011] Wesley Kerr, Paul Cohen and Anh Tran, Activity Recognition with Finite State Machines , *Proc. IJCAI'11 International Joint Conference on Artificial Intelligence* 22(2):1348-1353, 2011.

[Winarko and Roddick, 2007] Edi Winarko and John F Roddick. ARMADA – An Algorithm for Discovering Richer Relative Temporal Association Rules from Interval-Based Data. *Data & Knowledge Engineering*, 63:76–90, 2007.

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[Agrawal and Srikant, 1994] Rakesh Agrawal and Ramakrishnan Srikant. Fast Algorithms for Mining Association Rules. *In Proceedings of the 20th VLDB Conference*, 1994.

