Inexpensive user tracking using Boltzmann Machines[1]

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1 Introduction

Investigating the presence of a person near a display or in a particular area of the room can lead to improved system capacity by better energy saving or by raising the level of protection of the people (i.e. people privacy which is not assured with other types of sensors like cameras). In this paper [1], we tackle the inexpensive user tracking problem by using the Multi-integrated Sensor Technology (MIST1431), which comes at a low price. At the same time, we are aiming to address the lightweight learning requirements by proposing the *extended* Factored Conditional Restricted Boltzmann Machine (FCRBM), a form of Deep Learning, which incorporates a novel classification scheme.

The framework contributes on two main directions. The first is a technological one and consists in using a combination of MIST1431 and PIR, two low-cost and low-energy sensors. The second direction is a theoretical one, consisting in the introduction of a novel classification method for time series, namely Extended Factored Conditional Restricted Boltzmann Machines. This new technique builds on FCRBMs by incorporating a label layer and a classification procedure.

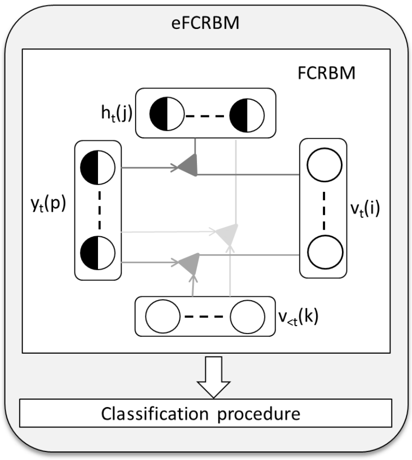

Figure 1: The general architecture of eFCRBM which include FCRBM (see [2]). The main differences between the proposed model and that of [2] are: 1) replacing the features and style layers with a class layer, and 2) the incorporation of a classification procedure.

2 Proposed Method

This section introduces eFCRBMs, shown in Figure 1. To enable classification and predictions in one unified framework, two modifications to FCRBMs are required. Firstly, a joint *class* layer which combines the style and feature layers of a FCRBM is introduced. Since conditioning on class labels is now possible, the machine thus constructed, can be used for predictions of time series belonging to different classes. Equipped with the ability to predict different class data, the second modification is the incorporation of a classification procedure. Based on the learned predictions, the classification procedure ensures an accurate partition to corresponding classes. Due to changes in the FCRBM structure, new mathematical details including, the energy function, probabilistic

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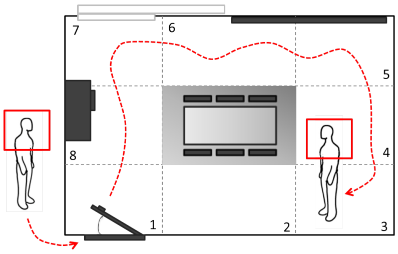

Figure 2: Experimental design: A room was split into eight locations. The sensor was placed either at a table or at the ceiling in the middle of the room.

	SVM	NB	AB	GMM	eFCRBM	
Artificial data (2 classes)	58.20	61.40	59.42	61.20	**80.52**	
Detection and Localization (17 classes)	70.45	70.98	30.15	74.92	**76.37**	S_1
	48.71	44.28	25.04	57.04	**60.09**	S_2
	64.77	42.21	28.54	65.34	**68.36**	S_3
Localization (16 classes)	71.56%	64.81%	40.21%	74.07%	**88.72%**	

Table 1: Comparison between SVM, Naive Bayes, AdaBoost, GMM and eFCRBM in terms of accuracy [%]. Each row represent a different problem or scenario [1].

inference, and learning/update rules are detailed in [1]. Furthermore, the novel classification scheme is based on the predicted values of eFCRBMs. More exactly, the main idea is first to fix the history layer to an arbitrary instance from the test data set. Predictions of the present frame using all possible classes are then performed. Finally, these predictions are compared with the true value TV_t of the present frame for that specific instance. To find the prediction closest to TV_t, a similarity or distance measure is then adopted. The class which made the closest prediction is chosen to be the class for that instance.

3 Experimental validation

We have assessed our approaches in three sets of experiments. In the first one, the goal was to classify artificial data points arriving from two trigonometric functions. The goal in the second set of experiments was the detection and localization of humans through data gathered from an MIST1431 sensor. Each gathered sample contained 14 outputs, such as six un-filtered ultra violet signals, six read and near-infra red part of the spectrum signals, temperature and humidity. A general experimentation protocol was designed (see Figure 2) for human detection and localization. Three situations were of major interest: 1) a person moving (i.e., M_i with $i = \{1, \ldots, 8\}$) in one of the eight positions, 2) a person standing still in one of the eight positions, or 3) the room is empty. Three scenarios were then recorded, such as S_1, S_2, S_3. Although successful, the previous localization and detection techniques still suffered from the following two problems: 1) inhibition of detection in the absence of ambient light, and 2) inaccuracies when it comes to people close to the display. Aiming at enhancing the quality of such estimates as well as at increasing the accuracy of localization, a method of fusing information from thermal and visible light sensors, i.e. PIR and MIST, has been developed and allows us to obtain results overnight. The method relies on motion detection in both signals and the results are depicted in the last row of Table 1.

4 Conclusion

In this paper we are proposing a novel framework capable to accurately detect and localize people in a room, including their level of motion. The framework contributes on two main directions. The first is a technological one and consists in using a combination of MIST1431 and PIR, two low-cost and low-energy sensors. The second direction is a theoretical one, consisting in the introduction of a novel classification method for time series, namely Extended Factored Conditional Restricted Boltzmann Machines. This new technique builds on FCRBMs by incorporating a label layer and a classification procedure. Artificial as well as real-world experiments clearly demonstrate the effectiveness of the proposed technique. Namely, eFCRBMs were capable of outperforming each of SVMs, GMMs, AdaBoost, and Naive Bayes classifiers, in all the tested scenarios.

References

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[2] Graham W. Taylor, Geoffrey E. Hinton, and Sam T. Roweis. Two distributed-state models for generating high-dimensional time series. *Journal of Machine Learning Research*, 12:1025–1068, 2011.