ERCIM "Alain Bensoussan"
Fellowship Scientific Report

Fellow:	Sundaram Suresh
Visited Location :	INRIA-Sophia Antipolis
Duration of Visit:	12 Months

I - Scientific activity

The research work carried-out during the 12 months of stay is development of online learning algorithm for automatic object and background separation and tracking the object in the video sequences.

Object tracking is a fundamental computer vision problem and is required for many high-level tasks such as activity recognition, behaviour analysis and surveillance. The main challenge in the object-tracking problem is the dynamic change in object/background appearance, illumination, shape and occlusion. An on-line learning neural tracker (OLNT) to differentiate the object from the background and also adapt to changes in object/background dynamics is proposed during my stay. A new neural classifier algorithm based on risk sensitive loss function is proposed to handle issues related to sample imbalance and change in characteristic of object class in future frames. The proposed neural classifier automatically determines the number of neurons required to estimate the posterior probability map. In the proposed learning algorithm, only one-neuron parameters are updated to reduce the computational burden during on-line adaptation. The tracked object is represented using an estimated posterior probability map. The signature of the posterior probability map is used to adapt the bounding box to handle the scale change and improper initialization. A set of experiments are conducted using benchmark videos to measure the robustness of the OLNT under change in appearance, rapid illumination change, scale/size change, improper initialization and occlusion.

In specific, the problem of tracking objects in video sequence is converted into a binary (object vs. non-object) classification problem. The developed online learning neural classifier algorithm is used to differentiate the object region from non-object region. The basic building block for the neural classifier is radial basis functions. The algorithm employs growing and pruning criterion based on class level deviation to evolve the network architecture based on the learning samples, which is different from the well-known sequential algorithms such as minimal resource network (MRAN), and growing and pruning radial basis function network (GAP-RBF). Also, the algorithm uses a risk sensitive loss function to handle the fewer samples and high imbalance in number of samples per class. The growing and pruning criterion is useful in learning the change in appearance. It has been proved that the truncated output of a neural classifier trained using a risk sensitive loss function approximates the posterior probability effectively. Hence, the estimated probability model obtained from an online learning neural classifier is used to create the probability map and the weighted average with target model is used to find the new location of the object. Then, we update the classifier parameters on-line. In addition, the size of the object window is determined using the signature of the probability map. This helps the proposed online learning neural tracker (OLNT) to handle the scale change and improper initialization.

A complete detail on learning algorithm and results from OLNT can be found in research article submitted to international conferences and IEEE Trans. on Pattern Recognition and Machine Intelligence.

II- Publication(s) during your fellowship

Please insert the title(s), author(s) and abstract(s) of the published paper(s). You may also mention the paper(s) which were prepared during your fellowship period and are under reviewing.

1. S. Suresh, Risk Sensitive Loss Functions for Sparse Multi-Category Neural Classifier, Int. Conference on Soft-Computing and Intelligent System, India, Dec, 2007.

Abstract:- The problem of high imbalance in number of samples per class and drift in distribution are quite common in multi-category classifications and they increase the estimation and learning errors significantly. The most commonly used loss functions in neural network literature such as mean square error, modified least square error, entropy do not perform well in these conditions as they minimize only the learning error and neglect the estimation error due to the imbalance and drift. Finding appropriate loss function to solve these problem are NP-hard. In this paper, we propose a new risk sensitive hinge loss function (RSHL), which minimize both the approximation and estimation errors. The adaptively estimated risk factor is integrated into modified hinge loss function. The modified hinge loss function minimizes the learning error and the adaptively estimated risk factor help in minimizing error due to imbalance and drift. The performance of the proposed risk sensitive hinge loss function is evaluated for satellite image classification problem. The results indicate the improved classification performance in terms of the overall accuracy as well as per class accuracy of the proposed risk-sensitive loss functions over many commonly used loss functions.

2. S. Suresh, F. Bremond, M. Thonnat and H. J. Kim, On-line Learning Neural Tracker, Submitted to IEEE Tran. On Pattern Analysis and Machine Intelligence, 2008.

Abstract:- Object tracking is a fundamental computer vision problem and is required for many high-level tasks such as activity recognition, behaviour analysis and surveillance. The main challenge in the object-tracking problem is the dynamic change in object/background appearance, illumination, shape and occlusion. We present an on-line learning neural tracker (OLNT) to differentiate the object from the background and also adapt to changes in object/background dynamics. A new neural classifier algorithm based on risk sensitive loss function is proposed to handle issues related to sample imbalance and change in characteristic of object class in future frames. The proposed neural classifier automatically determines the number of neurons required to estimate the posterior probability map. In the proposed learning algorithm, only one-neuron parameters are updated to reduce the computational burden during on-line adaptation. The tracked object is represented using an estimated posterior probability map. The signature of the posterior probability map is used to adapt the bounding box to handle the scale change and improper initialization. We describe experiments using benchmark videos to measure the robustness of the OLNT under change in appearance, rapid illumination change, scale/size change, improper initialization and occlusion.

III -Attended Seminars, Workshops, and Conferences

Please identify the name(s), date(s) and place(s) of the events in which you participated during your fellowship period.

1. Presented a talk on “Risk Sensitive Hinge Loss Functions” in International Conference on Soft-Computing and Intelligent System, Dec., 27-29, 2007.