ECCV 2012
European Conference on Computer Vision 2012
October 7-13, 2012, Firenze , Italy

Reviews For Paper

Track	Main Conference
Paper ID	1617
Title	Timely Object Recognition

Masked Reviewer ID: Assigned_Reviewer_1
Review:

Question	
Provide a brief description of the contribution and explain your overall assessment by listing positive and negative points.	This paper presents a method for sequencing a set of object detectors to accomplish a multi-object classification task. The idea is to try to get as much information about objects in the scene before a timer runs out. It may be worthwhile to use some poor, but fast detectors rather than better but slower detectors in order to maximize the total value of the overall object detection. The problem is formulated using a reward optimisation framework with a sequential model giving beliefs over the multiple classes, and actions corresponding to detectors. Positive points: This idea I think is novel in the specific context applied here (multiple object recognition). The results look promising Negative points: The problem is poorly formulated and the results have no statistical significances associated with them, making it hard to figure out what is going on. Missing discussion of references to related work in active sensing (even though these are included!)
Novelty	Moderately original
Explain your novelty rating and provide relevant citations if you find it incremental or done before.	This idea I think is novel in the specific context applied here (multiple object recognition), but has been explored in depth in the RL literature (as active sensing), and this is not discussed in the paper.
Technical correctness. Is the manuscript technically sound?	Has major problems
	The problem is formulated apparently as a partially observable MDP (or at least it is just begging to formulated as such), and I would suggest the authors look into this more closely. References [25-27] are good starting points, as well as the work by Andreas Krause on active sensing. It seems the authors of this paper are aware of this connection, but have not exploited it (or even discussed it), even though they reference some relevant work. A POMDP formulation of this problem would include variables C for each class, observations for each variable (and would even admit multiple different observations for each class, corresponding to

Technical comments: Explain your assessment of technical correctness.	different detectors/sensors of varying quality/cost), and actions as indicated in the paper. An additional "resource" variable could then be used to model the time bound, which, once exhausted would stop the process. The reward functions could be as specified in the paper. Given such a formulation, a large body of work on POMDP solution techniques (include the linear approximations and policy iteration methods proposed) could be leveraged and compared. It may also be possible to formulate this problem as a constrained MDP (CMDP). - section 4.1 was unclear to me - why is there a fully connected MRF being used here? I suppose that this is modeling the relationships between different classes in some way, but this is never explored or discussed. The belief updates over multiple detections are also not described, as indicated in figure 2. Figure 3 is unclear - what does it mean that "one action has already been taken"? I suppose the shaded node has something to do with this, but this is never explained. There are no connections shown to a previous time step as in Figure 2.
Experimental Validation.	Insufficient
Explain your assessment of experimental validation.	- the use of a discount factor is not a problem, but this is never described in the experimental results - what value of lamba was used? - The lack of error bars in figures 5 and 6 was dissapointing, and would be necessary to show that this model is actually having an effect - how many images were used for training/validation/testing? How many object categories? - does "manual" in the figures 5,6 correspond to "random" in the text?
All other comments including clarity of presentation, any missed references, supplemental material.	see above
Overall Rating.	Probable Reject
Adherence to submission guidelines (paper length, anonymity, double submission, supplementary material). If a violation is suspected, contact the program chairs (eccv-2012-program-chairs@googlegroups.com) immediately. You must continue to review the paper as if guidelines were followed until the PCs say otherwise.	Adheres to guidelines

Masked Reviewer ID: Assigned_Reviewer_2
Review:

Question	
Provide a brief description of the contribution and explain your overall assessment by listing positive and negative points.	The paper proposes to develop a dynamic policy for selecting classifiers or detectors to achieve the highest recognition performance under the evaluation metric of performance vs. time. A multi-class recognition policy system is constructed by repeatedly selecting an action from a set of actions, executes it, potentially receives an observation, and selects the next action. The set of actions can include classifiers, detectors, or hybrid actions (detector followed by classification of its output). Overall, the framework/system is described clearly. The problem is novel and definitely of interest to the vision community. However, on the down side, the experiment validation is far from sufficient. There is no comparison to existing algorithms or state-of-the-art on the datasets tested. For example, is it possible to compare best performance of any time, average performance between the start time and end time, and the performance with the same testing time to Felzenszwalb's algorithm on PASCAL VOC? Lots of details were omitted. For example, what's the number next to the legend? How many points were evaluated? In addition, experiment results are not clearly explained. E.g. why detection curves are very similar to classification curves.
Novelty	Very original
Explain your novelty rating and provide relevant citations if you find it incremental or done before.	Novel
Technical correctness. Is the manuscript technically sound?	Appears to be - but didn't check completely
Technical comments: Explain your assessment of technical correctness.	N/A
Experimental Validation.	Insufficient
Explain your assessment of experimental validation.	see 1
All other comments including clarity of presentation, any missed references, supplemental material.	see 1
Overall Rating.	Borderline Poster/Reject

Adherence to submission guidelines (paper length, anonymity, double submission, supplementary material). If a violation is suspected, contact the program chairs (eccv-2012-program-chairs@googlegroups.com) immediately. You must continue to review the paper as if guidelines were followed until the PCs say otherwise.	Adheres to guidelines

Masked Reviewer ID: Assigned_Reviewer_3

Review:

Question	
Provide a brief description of the contribution and explain your overall assessment by listing positive and negative points.	The authors use the reinforcement learning framework to learn a policy that decides (at run-time) the order in which class-detectors are run to get good detection and classification results quickly. The idea is interesting, the presented results look promising, however the presentation of model/algorithms and evaluation is very unclear.
Novelty	Very original
Explain your novelty rating and provide relevant citations if you find it incremental or done before.	This topic does not appear to have been explored much in the literature.
Technical correctness. Is the manuscript technically sound?	Appears to be - but didn't check completely
Technical comments: Explain your assessment of technical correctness.	Appears to be - but didn't check completely
Experimental Validation.	Insufficient
Explain your assessment of experimental validation.	The method is evaluated on only one dataset. The experimental setup is not thoroughly explained. Little effort is made to analyse the policies that the model learns. Precise meanings of the curves is difficult to establish (due to poor legend labelling). Comparison of the two reward functions is not thorough. Choice of belief model is not motivated by the experiments.
	- Line 43: 'large photo collection' -> 'large photo collections'. - Figure 5: unclear what the legend means. - Line 414: 'As shown in Figure 5' -- unclear which is the random policy.

All other comments including clarity of presentation, any missed references, supplemental material.	- Figure 5: what happens past 20s? - Line 513: Missing Conclusions section? - Good to list contributions in Introduction. - Good to frame approach more clearly within the standard Reinforcement Learning framework. - Line 164: 'for the same reason as' -- what is this reason? - Line 168: What does the real valued observation o_i signify? (i.e. what does the RL 'agent' observe?) What is O_i? What is P(O_i)?
Overall Rating.	Probable Reject
Adherence to submission guidelines (paper length, anonymity, double submission, supplementary material). If a violation is suspected, contact the program chairs (eccv-2012-program-chairs@googlegroups.com) immediately. You must continue to review the paper as if guidelines were followed until the PCs say otherwise.	Adheres to guidelines