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Short Communication

Features classification based on redundancy segmentation in observing minute details group

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ABSTRACT

Context helps a learner to learn about the world. Context can start as a shallow understanding of a situation, place, scene or conversation. This shallow understanding allows a learner to draw connections to previously acquired knowledge, and to specialize a context if necessary. Learning must take advantage of redundancy, and context allows redundancy to be identified. Context can help one make a quick judgment of novelty. In a new situation, the learner should tread more carefully, observing minute details in order to make sense of the complex whole. When exposed to a similar situation, however, the learner can build upon the work done during the previous encounter.

Keywords: Image classification, lateral information, robust feature extraction and generation.

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INTRODUCTION

In order to maximize the benefit of reuse, the learner must be able to judge novelty as quickly as possible. In addition, such judgments should be robust to minor changes. For example, if the learner has visited many forests without flowers but none with flowers, the learner should still be able to connect a forest with flowers with previous forest encounters. The ability to make this connection is important and allows the learner to quickly learn that forests can contain flowers. The model based approach allows associations to be made between visual contexts without supervision. This is because the approach takes into account image structure and content in a form that is invariant to changes with little or no effect on context, such as minor changes to scale and position. The complexity of the representation is also important for learnability. If we compare this approach to one used by Carson et al. (1999), Chun and Jiang (1998) and Henderson and Hollingworth (1999), the strengths and weaknesses of this complexity become clear. Lipson (1996) and Sedghi (2013) reduce context to an N-dimensional feature vector, where $10 < N < 100$. The approach is appealing because the reduction is very straight forward, the outputs of filters are examined to find principal components. These principal components characterize almost all of the variation between natural scenes. The context is only one step away from low-level features. The model-based approach requires an image to be reduced into components that correspond to elements of the scene. Unfortunately, segmentation is a problem that is far from being solved. To make matters worse, the problem is under constrained. Two different scenes can yield the same two-dimensional pictures. For example, any texture in a scene could be the result of small variations in depth or could be shading that is painted on to a surface. At best, we can make an educated guess by taking advantage of regularity in the world. The most effective segmentation techniques take advantage of color, texture, edges, and stereo data. For each image to be segmented, pixels must be classified into groups. Thus, context is many steps away from low-level features. However, if we assume that all of these issues can be swept under the rug, the model-based approach offers learnability advantages because of its invariance properties.

METHODOLOGY

A context system based upon a feature vector will project to some Euclidean space. In order to learn a vector-

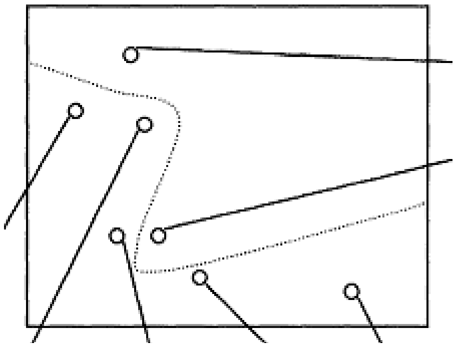

Figure 1. Complex classifiers may be necessary to learn from vector-based contexts.

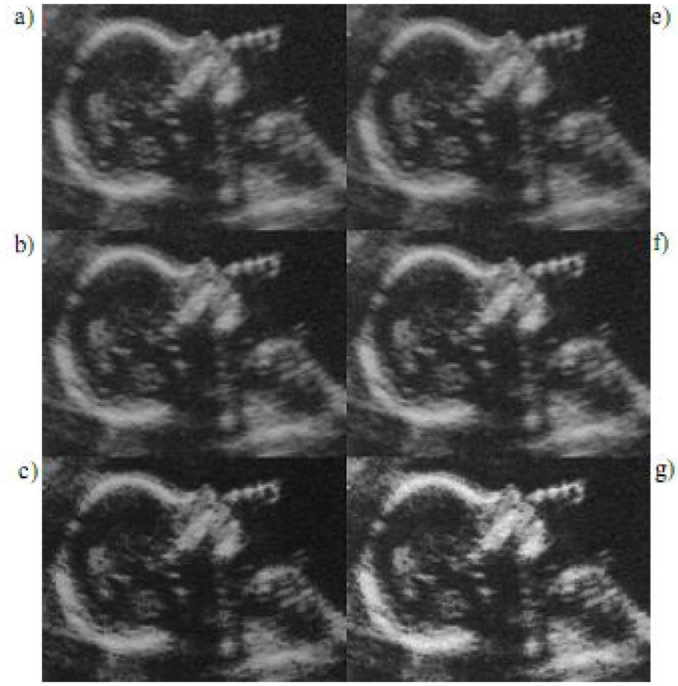

Figure 2. Image processing with proposed method in five different levels.

based context, the space needs to be carved up. There are many existing methods for learning classifiers, such as support vector machines, neural networks, and decision trees. If the image space dimensionality is reduced incorrectly, certain context may overlap or images with the same context may be spread apart. As the sketch in Figure 1 demonstrates, the required classifiers may need to be fairly complicated to fit the data. Even if all of these processes are easy, one problem still exists: we need tons of supervised data. In the real world, a child is not always given a label for a scene. Thus, they need a more effective way of tying contexts together. The model-based approach does not require extensive supervision. Contexts are tied together by using scene content and structure. The models are descriptive enough that they can be compared. Additionally, the models lend themselves to introspection. As more is learned about the context, elements of the model can be given labels, like "'sky" or "ground." This opens up the way for explanation based learning. The model-based representation is expensive to form. Texture segmentation is a hard problem that may require a great deal of computation. The vector-based representation is simple and is computationally cheap to build (Sedghi, 2013; Sedghi, 2012). However, model based contexts are easier to learn than vector-based contexts. Clearly, each method has its tradeoffs. However, it may be possible to design a system in which these two methods bootstrap each other. Vector-based context can be used to find candidate context clusters by using nearest neighbors and the model-based approach can be used to edit these clusters. Also, the model-based approach can be used to tie together similar contexts that are far apart in the visual context space. Segmentation is key to the model-based approach.

RESULTS AND DISCUSSION

A poor segmentor will make learning impossible; a good segmentor will make learning easy. A good next step for producing effective model-based context is to develop a segmentation system specifically for the model-based approach. Such a segmentor would ignore small elements and would parse out large and salient scene components. The segmentor should be capable of a modal completion, if two area of similar consistent texture are split by another region they should be merged into a single region. A few people standing on a field should not cut the field up into multiple image regions. Stereo and edge extraction can be used to find occluding contours, a particularly compelling division of scene segments. An alternative approach is to specialize segmentation. This process would involve learning and applying texture detectors. Figure 2 shows image processing with proposed method in seven different levels. These detectors could be used to find small neighborhoods of pixels that correspond to specific textures. The textures learned and applied by the system would be ones that occur commonly in scenes, such as "plant-like texture" or "building-like texture." Context's ability to reduce the ambiguity of an input signal makes it a vital constraint for understanding the real world. It is specifically examined the role of context in vision and how a model-based approach can aid visual search and recognition. Figure 3 shows the block diagram of signal estimation in classification. Through the implementation of a system capable of learning visual context models from an image database, I demonstrate the utility of the model-based approach. The system is capable of learning models for "water-horizon scenes" and "suburban street scenes"

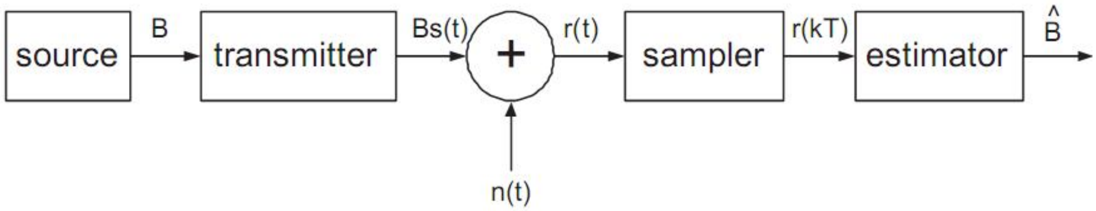

Figure 3. The block diagram of signal estimation in classification.

from a database of 745 images.

Conclusions

In this paper, a system was implemented that generates blobs from images and uses blob matching and image clustering to learn visual context models. The system has learned models for "water-horizon scenes" and "suburban street scenes", and motivated the need to learn visual context and the utility of model-based visual context. In addition, it has discussed methods by which models can be learned; and also discussed how visual context can be applied to visual search and recognition tasks and have provided arguments for how model-based visual context can improve these applications.

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