MOTION ANALYSIS USING THE NOVELTY FILTER

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Abstract

An original approach to the motion analysis, based on the novelty filter, is proposed. The novelty filter stresses the novelties occurring in a pattern representing an image of the scene under consideration with respect to patterns representing previous images of the same scene, so that visual information about the motion of the objects is obtained. The novelty filter may be implemented by a neural network architecture, taking advantage of the capabilities of massive parallelism, adaptive learning and noise robustness. The novelty filter may learn the entire trajectory of an object, through an incremental learning of a sequence of images capturing the scene, thus emphasizing if the position of the object in an image belongs to the learned trajectory. If the position of the object does not belong to the trajectory, the network gives information on the shift from the trajectory.

Key words: Motion analysis, novelty filter.

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1. Introduction[1]

From the computational point of view, the most popular approaches to the analysis of object motion are based on the optical flow process (see e.g. (Horn, 1986)) and the correspondence process (Ullman, 1979). These and other types of motion measurement pose significant problems, both theoretical, such as the aperture problem or the ambiguity, and practical, such as the continuity of the motion in the image.

It must be noted that accurate motion measurements are in most cases not necessary. Some important visual tasks require to compute only certain properties of the velocity field: motion must be simply detected, but not measured, for example, to respond quickly to a moving object.

An original use of the novelty filter (Kohonen and Oja, 1976; Oja, 1979; Kohonen, 1984) for detection of motion is described. The novelty filter stresses the novelties present in an intensity pattern, with respect to the sequence of previous input patterns, in order to extract useful information about the motion of objects in the image (Ardizzone et al., 1990). An interesting feature of the novelty filter is its simple implementation by a neural network architecture (Kohonen and Oja, 1976) taking advantage of the capabilities of massive parallelism, adaptive learning and noise robustness.

In the following, in Sect. 2 some theoretical remarks on the novelty filter operations are outlined, in Sect. 3 the application of the novelty filter to motion analysis is described and in Sect. 4 an implementation of the novelty filter along with some preliminary results is described.

2. The novelty filter

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The novelty filter shows the novelties in an input pattern with respect to previously learned patterns. Furthermore, the novelty filter can distinguish the missing parts from the added parts in the input pattern with respect to the previously learned patterns.

The novelty filter may be implemented by a simple neural network architecture made up of a single layer of linear units interconnected by a feedback connection (see fig. 1). The overall transfer operator is described by the following equation:

$$\tilde{x} = x + M\tilde{x} = \Phi x$$

It is possible to show how an architecture using the feedback connections guarantees a better convergence with respect to an analogue architecture with no feedback connections.

* * * * * * FIG. 1 NEAR HERE * * * * *

During the learning phase the filter adapts itself to the proposed input patterns. During the working phase the filter stresses the novelties in the input pattern with respect to the previously learned patterns. The learning phase follows an anti-Hebbian rule: the feedback matrix has the following state equation:

$$dM/dt = -\alpha\, \tilde{x}\tilde{x}^T$$

where the parameter α is adaptively modified during the learning phase.

From theoretical and experimental analysis (Chella and Morreale, 1990) it has been found that α may be interpreted as a measure of the similarity of the pattern under consideration with respect to the previously learned patterns.

When the current learning pattern is similar to a previously learned pattern, α must be incremented to allow the attention of the novelty filter to be focused on the novelties in the current pattern. Therefore the parameter $1/\alpha$ represents a convergence index of learning: when $1/\alpha$ approaches zero the filter is close to convergence.

3. The novelty filter in motion analysis

An original application of a neural network implementation of the novelty filter in motion analysis is described. The application is related to the extraction of information on the motion of objects in a scene.

When a pattern representing the position of a moving object is shown, visual information on the motion of the object is extracted by detecting the novelties in the image with respect to patterns related to previous positions.

During the learning phase, sequences of frames representing the trajectory of the moving object are shown to the novelty filter. During the working phase a new frame representing the object in a certain position is shown in input to the filter; the output represents the novelties between the presented pattern and the learned trajectory. It is then possible to investigate if a certain position of the object is on the learned trajectory: in this case the novelty filter displays the differences between the position of the object and the learned trajectory.

When a full white pattern is presented to the input, all the learned patterns are treated as novelties with respect to the input pattern; the entire trajectory previously learned by the filter is then stressed.

It is also interesting to outline not only the novelties with respect to the closest pattern but, due to the cross-talk effect from the other learned patterns, also the novelties with respect to the whole trajectory, that may be considered as a single image learned by the network.

Some interesting points may be outlined about the convergence process of the novelty filter. In fact it is not necessary to obtain the strict convergence of the filter: it has been found (Chella and Morreale, 1990) that interesting results may be obtained by maintaining the convergence index $1/\alpha$ as a constant. In this case, strict convergence is not obtained and the output of the novelty filter contains, along with the novelties in the image, information on the previously learned patterns, as in an autoassociative memory. When a new pattern is shown it is then possible, by suitably tuning the parameters of the output representation such as threshold, range of gray levels etc., to emphasize the novelty filter operation along with the autoassociative memory operation. This property allows e.g. to recall a previously learned trajectory from a single frame.

Since the factor $1/\alpha$ is approximately constant during the learning phase, it is possible to replace α with $\eta*\alpha$, where η is a factor externally defined. When η decreases monotonically with the number of learning steps, visual information on the temporal evolution of the object motion is obtained: the learning action on the first patterns is stronger than the learning action on the last patterns.

It is also possible to treat the motion of many objects whose trajectories cross each other: trajectories belonging to different objects present different gray levels at the intersection points.

4. Implementation and preliminary results

A program simulating the neural network architecture operating as novelty filter has been developed in PASCAL using the GKS package for the graphical interface; it currently runs on a Digital VaxStation II/GPX under VAX/VMS.

Input patterns are obtained as arrays made up of 512*512 integers in the range [0...255]; they are first reduced to arrays made up of 64*64 integers in the range [0...9] and then the array elements are normalized as real number in the range [0..1] and displayed in a window with 64 gray levels.

The learning phase may be carried out interactively on the current input pattern, or in batch on a set of input patterns previously specified. In this case it is also possible to specify the learning parameters and the temporal evolution of the motion. The test phase may be carried out either by presenting an external test pattern or by presenting a full white pattern.

The graphic interface of the program produces three output pattern windows: the positive output pattern window representing the novelties related to the added parts, the negative output pattern window representing the novelties related to the missed parts and the superimposition window. It is possible to interactively define the threshold and the range values of gray levels used for the output graphic representation to stress e. g. the autoassociative memory operation with respect to the novelty filter operation.

During the learning phase of a trajectory, sequences of patterns representing the same object in several positions have been generated in the same way as a sequence of movie frames representing the object during its motion. In particular the silhouette of an airplane has been used as the moving object (see fig. 2).

* * * FIG. 2a NEAR HERE * * * * * * FIG. 2b NEAR HERE * * *

* * * FIG. 2c NEAR HERE * * * * * * FIG. 2d NEAR HERE * * *

In fig. 2a the output of the novelty filter is shown when a full white pattern is presented. In the superimposition window the trajectory of the object during motion is displayed and in the positive output window the superimpositions with temporally close patterns are stressed. Fig. 2b shows the output when a pattern representing the object in a position belonging to the trajectory is presented. In the negative output window the recognition of the position of the object is displayed. Fig. 2c shows the output of the network when a pattern representing the object in a position not belonging to the trajectory is presented. It is possible to deduce the shift of the object necessary to make it re-enter in the previously learned trajectory: from the most bright pixels in the negative output window to the most bright pixels in the positive output window. Fig. 2d shows an example of the superimposition of the novelty filter operation along with the autoassociative memory operation. A pattern representing an object with a missed part is used to recall the entire trajectory.

Fig. 3 shows some results by replacing, during the learning phase, α with $\eta*\alpha$, where η is a factor externally defined. As previously noted, if η monotonically decreases with the number of learning steps, it is possible to obtain visual information on the temporal evolution of the object motion. In particular, fig. 3 represents two linear mutually crossing trajectories.

* * * FIG. 3a NEAR HERE * * * * * * FIG. 3b NEAR HERE * * *

Fig. 3a shows the output of the network when a full white pattern is presented. Note the variations of the brightness of the objects according to the temporary evolution of the trajectory. At the cross point it is possible to distinguish between the two trajectories. Fig. 3b shows the output of the network when a pattern representing the object in a position corresponding to the cross point of the two trajectories is presented. In the negative output window the recognition of the position of the object is displayed.

5. Conclusions

At present, the application of the novelty filter to motion analysis is limited to planar motion; a generalization to 3-D motion analysis using a 3-D novelty filter is currently under development.

The input of the 3-D novelty filter is a 3-D array representing the volumetric reconstruction of the moving object; the output of the novelty filter is a 3-D matrix representing the novelties in three dimensions.

In the version of the 3-D novelty filter under development, sensory data are 2-D digital images (bidimensional arrays of pixels) representing one or more views of the observed scene. The volumetric reconstruction of the object is a representation of the type of spatial arrays (a voxel representation); this is currently obtained by applying classical volume intersection techniques to infinite generalized cylinders grown up from silhouettes of different scene views (Ardizzone et al., 1989).

The output of the filter is also a spatial array in which the novelties in the position of the object with respect to previously learned positions are stressed. In spite of the computational load, first results of this generalization to 3-D motion analysis appear interesting; they will be more extensively treated in future work.

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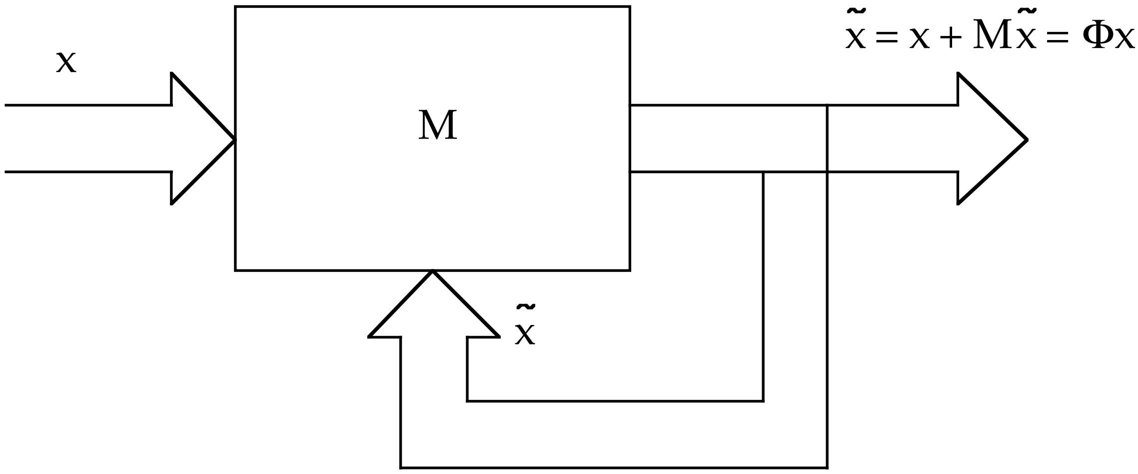
FIGURE CAPTIONS

Fig. 1 - The novelty filter architecture.

Fig.2. - Outputs when α is constant. (a) Output when the full white pattern is presented. (b) Output when the position of the object belongs to the trajectory. (c) Output when the position of the object not belongs to the trajectory. (d) Output when the entire trajectory is recalled.

Fig. 3 - Outputs when α is replaced by $\eta * \alpha$. (a) Output when the full white pattern is presented. (b) Output when the position of the object belongs to the cross point of the two trajectories.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