OPTICAL FLOW FOR CARS OVERTAKING MONITOR: THE REAR MIRROR BLIND SPOT PROBLEM

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A fundamental goal of an overtaking monitor system is the segmentation of the overtaking vehicle. This application can be addressed through an optical flow driven scheme. We focus on the rear mirror visual field using a camera on the top of it. If we drive a car, the ego-motion optical flow pattern is more or less unidirectional, i.e. all the static objects and landmarks move backwards. On the other hand, an overtaking car generates an optical flow pattern in the opposite direction, i.e. moving forward towards our car. This makes motion processing schemes specially appropriate for an overtaking monitor application.

We have implemented a highly parallel bio-inspired optical flow algorithm and tested it with real overtaking sequences in different weather conditions. We have developed a post-processing optical flow step that allows us to estimate the car position. We have tested it using a bank of overtaking car sequences. The overtaking vehicle position can be used to send useful alert signals to the driver.

1. INTRODUCTION

The work presented in this paper has been developed in the framework of ECOVISION European Research project (ECOVISION (2003)). One of the objectives of ECOVISION consortium is the development of a pre-cognitive visual model that can be useful for real world problems. In particular, the rear-view mirror blind spot monitor is presented as a feasible problem in which motion processing can provide useful cues for the overtaking car segmentation.

The blind spot in the rear-view mirror is source of multiple accidents. A camera can be placed in the car allowing us to detect, using optical flow algorithms, the overtaking car. This can be used to send alert signals to the driver. The optical flow driven scheme has several properties that can be very useful for car segmentation. Basically, in the optical flow, we should find static objects moving backwards (due to our ego-motion) and the overtaking cars moving forward towards our vehicle. We should take into account the perspective deformation. The optical flow of a moving object is not homogeneous, the parts of the object that are far away from the camera seem to move slower than the ones that are closer, so you can find a set of different velocities, which changes continuously, along the same object.

Finally, the proposed algorithm has to be robust enough to detect movement in a non static camera. The movement of the host vehicle is a very important source of artefacts and for the application addressed here its is critical that the algorithm used can *"clean"* this noisy patterns.

The work scheme that we have developed is composed of two very different stages. In the first step, using a bio-inspired model, we compute the optical flow. Second, using very simple filtering operations and optical flow templates, we get a saliency map that can be used to estimate the car position in the image.

To finish the paper, we show some results of the proposed system for several overtaking car sequences.

2. BIO-INSPIRED MODEL FOR COMPUTING OPTICAL FLOW

The model we proposed is based on the Simoncelli & Heeger model (Simoncelli (1993), Simoncelli, Heeger (1998), Díaz, J et al (2003)) which describes the processing that takes place in cortical areas V1 and MT. The computation scheme is highly parallel and regular, and the resultant model can be seen as energy based optical flow algorithm.

The motion estimation is computed by the cortical cells. V1 simple and complex cells apply for space-time orientations selectivity as in other models (Grzywacz, Yuille (1990), Heeger (1987)). MT cells are modelled combining the outputs of a set of direction-selective V1 complex cells whose preferred space-time orientations are consistent with the MT cells characteristic velocity. The mechanism for velocity selectivity can be described in the spatio-temporal domain easily. The basic idea is that the power-spectrum of a translational pattern lies on a plane in the space-time domain and the tilt of the plane depends on the velocity. In this way, we can tune each MT velocity-selective neuron summing responses of a particular set of V1 neurons whose spatio-temporal bands intersect with this plane (Watson, Ahumada (1983)). Other V1 neurons tuned to different planes also contribute with a weighted sum.

The original Simoncelli model (Simoncelli (1993), Simoncelli, Heeger (1998)) uses Winner Takes All configuration among the MT population to select the estimated velocity. Instead of it, our model uses a Some Winners Take All mechanism. The estimated velocity is a weighted sum of the neurons with responses close to the maximum, as it is shown in Fig 1. This is more consistent with physiological data and allows us, with less MT velocity tuned neurons, to compute more accuratelly the velocity of a motion pattern.

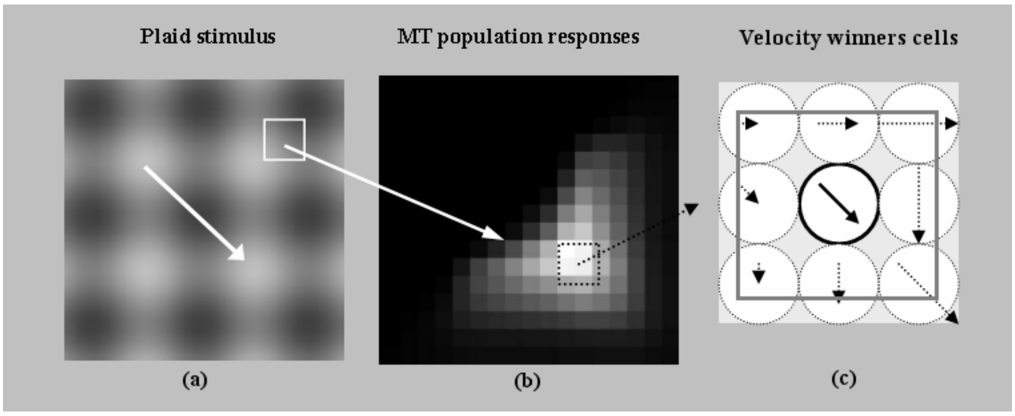

Fig. 1. Population response example. The result of a plaid stimulus composed by a sinusoidal grating moving rightwards and another one moving downwards is a moving pattern toward the right-bottom corner (a). A set of MT neurons responses are codified using grey levels. The relative position of the winner element with respect to the centre of the population represents

the velocity module and direction. Maximum responses are given at the best tuned MT neuron for that stimulus, but MT cells tuned to near velocities are not zero. We use Some Winners Take All mechanism to estimate reliably the velocity in presence of noise (b). Finally, the winner elements are those with responses close to the maximum response element (c).

One of the parameters of the optical flow algorithm is the spatio-temporal scale of the filters. To discriminate small objects we need small filters and bigger filters for bigger objects (if this is not taken into account we suffer of errors and aperture artefacts). In our model, this can be controlled changing the receptive field of V1 neurons. Simoncelli and Heeger (Simoncelli (1993), Simoncelli, Heeger (1998)) proposed a multi-scale computation of the V1 cells using three scales and a weighted sum of them.

According to this idea, in the overtaking car application, we adopt a scale-integration that uses the perspective deformation to combine the different scales. The basic idea is to use small receptive fields in the left side of the image (far visual field) and bigger fields in the right side (closer visual field). This can be seen like as an artificial fovea in the far visual field where high spatial resolution is desirable. The sum of the scales is computed using a combination of Gaussian weight functions of the image columns. The combination steps are illustrated in Fig 2 and the represented equation (1) is:

$$W_s = \exp\left[-(col-\mu_s)^2 \Big/ (2*\sigma_s^2) \right] \qquad V1_{eq} = \frac{\sum_s W_s * V1_s}{\sum_s W_s} \qquad (1)$$

where “s” indicates the scale, “μ” the spatial position in which this scale is centered, “σ“ the scale variance and “col” the current image x position.

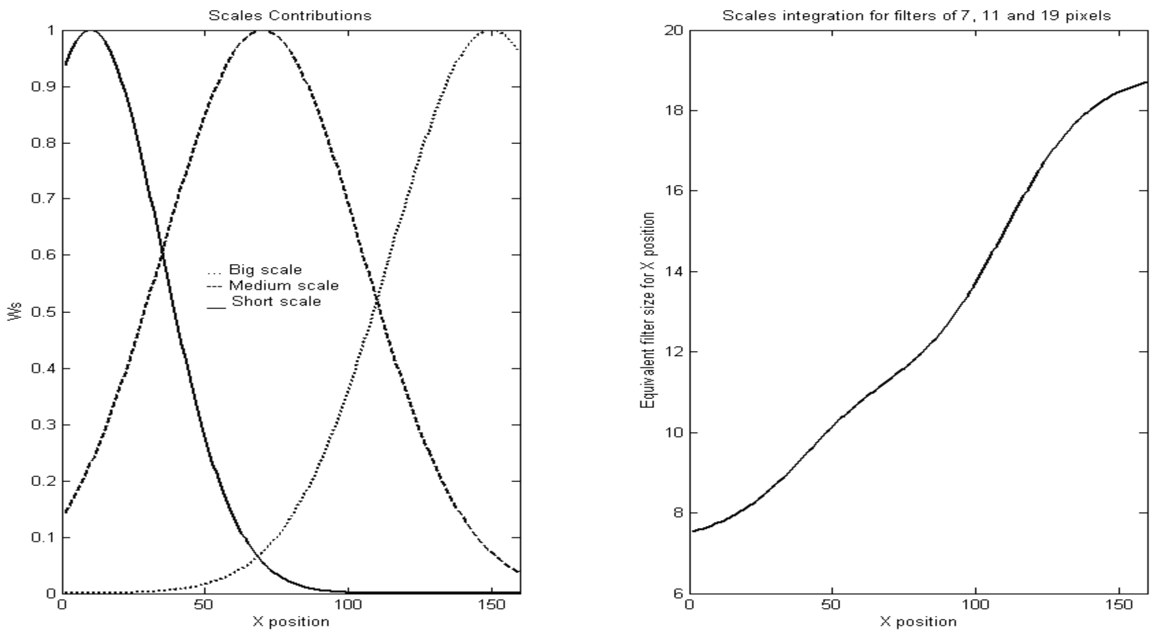

Fig. 2. Spatio-temporal scales integration. The left plots represent the weighted values of the scales contribution in each image x position. Three scales of symmetrical receptive fields of 7, 11 and 19 are used for the overtaking application. The weights are Gaussians. The equivalent filter scales as a function of the X position in the visual field are shown in the right image

2.1. Model implementation

The implementation of the optical flow algorithm proposed can be summarized in 5 steps:
1. Computing local stimulus contrast.
2. Modelling simple and complex V1 neurons, using spatio-temporal third Gaussian derivatives and spatial pooling. This is done at three scales.
3. Combining the scales to adapt the computation to the rear view mirror perspective
4. Modelling MT neurons summing the weighted responses of V1 cells which lie on its characteristic plane in the space-time domain.
5. Computing the velocity estimation for each pixel in the visual field using a weighted sum of winner neurons.

The scheme in Fig. 3 illustrates the algorithm steps and the result.

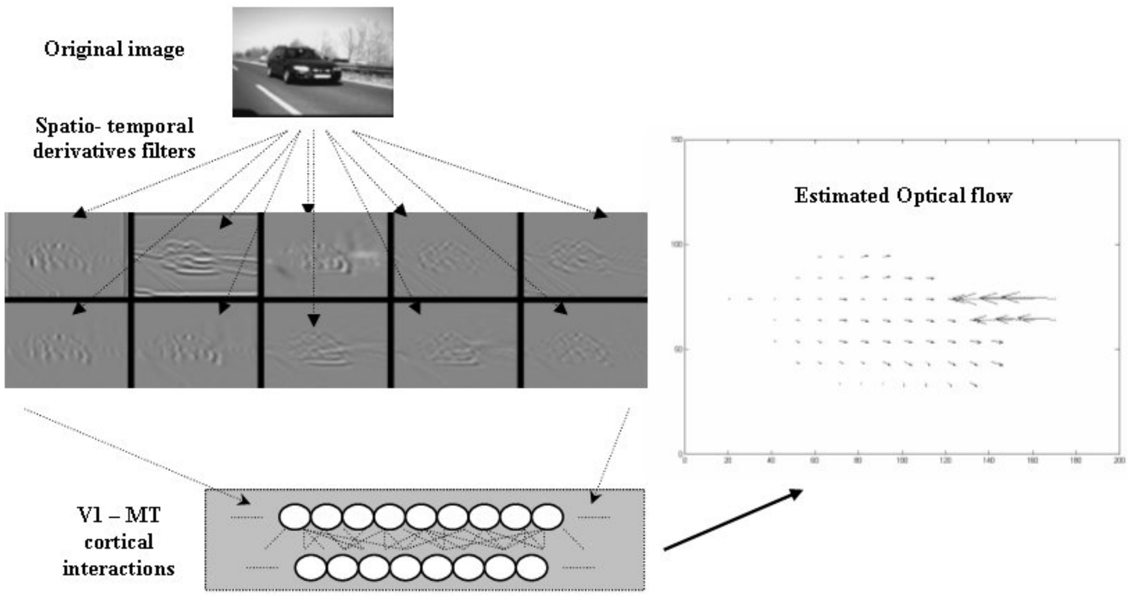

Fig. 3. Optical flow model scheme. An overtaking car sequence is used to evaluate the model. The basic set of third Gaussian derivatives composed of G_{xxx}, G_{yyy}, G_{ttt}, G_{xxy}, G_{xyy}, G_{xxt}, G_{xtt}, G_{yyt}, G_{ytt} and G_{xyt} are computed. This pre-filtered images are combined to get V1 spatio-temporal orientation simple cells. Spatial pooling is used to get V1 complex cell responses and their combinations with different scales give us the MT cell response. Finally, for each pixel the same winners take all scheme is considered the estimate the velocity vector.

One drawback of energy based optical flow algorithms is that they are of high computational cost but, the hardware implementation of the algorithm proposed is very parallel and regular. ASIC or FPGA devices can take advantage this inherent parallelism to compute, in a regular and fast way, the optical flow. Furthermore, the fact of using multiple velocity channels (one for each V1 neuron), gives us a robust method to get reliable motion pattern detectors. This also makes the model more capable to work with rotation and other object deformations. Another very interesting property of the algorithm is the uniform optical flow that it generates (see Fig. 4). Even for not static camera sequences, in which due to the pothole we may receive very noisy sequences. This is not the most accurate optical flow algorithm but it provides quite uniform patterns that facilitate the car segmentation in posterior processing steps.

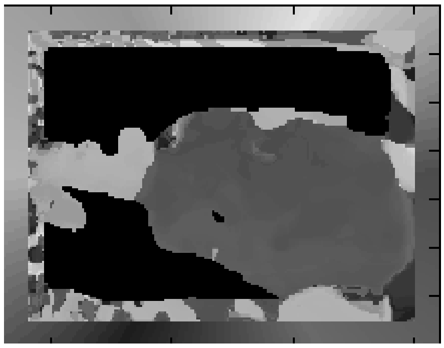

Fig. 4. Car segmentation using optical flow. Dark greys represent rightward movements (the car) and light greys leftward motion (the landscape). We can see that the proposed model gives us a very uniform object segmentation therefore car tracking can done easily.

3. CAR TRACKING: POST-PROCESING OPTICAL FLOW STEPS

The proposed application needs the generation of alerts signals to the driver to prevent traffic accidents. A post-processing step have been added to estimate the car position. The computation steps are:

1. Considering only rightwards movements. While the overtaking manoeuvre, the overtaking car is moving to the right side of the image so we do not need to considerer leftward velocities.
2. Only uniform velocity pixels are allowed. We supposed that the overtaking car has, locally, similar pixels velocities in neighbour pixels (relaxed rigid body motion assumption). This assumption effectively cleans the optical flow.
3. Templates to detect the car. We use very simple and general templates, squares and rectangles to detect the car position. Correlation with these templates gives us a saliency map of cars points that will be used in the next step to compute the vehicle position using a centroid computation. The idea is illustrated in Fig. 5.

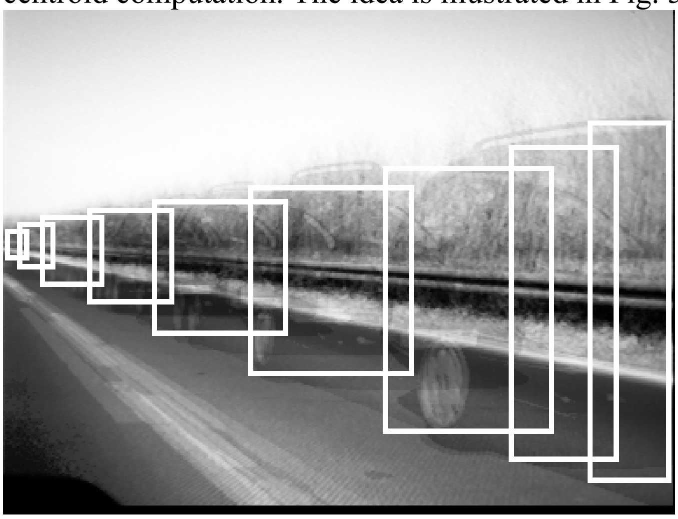

Fig. 5. Templates for car tracking based on optical flow. After filtering the optical flow that we obtain, we use templates based on squares and rectangles to estimate the car position. The saliency map will be the central points of the car.

The template size and form depends of the x position. The template correlation processing will neglect any pattern considerably smaller the corresponding template size at this x position. It allows to get more reliable estimation of the car when it is closer to us (and it seen as a big object), which is the dangerous and important situation that we intend to detect.

4. Finally, we estimate the car position computing the centroid of X and Y coordinates of the remaining pixels of the previous saliency map. We use a very basic Kalman filter state equation to apply some centroid inertia.

3. RESULT EXAMPLES

We have tested the algorithm in different overtaking car sequences provided by Hella. We have uses different cars and whether conditions getting very promising results (see Fig. 6).

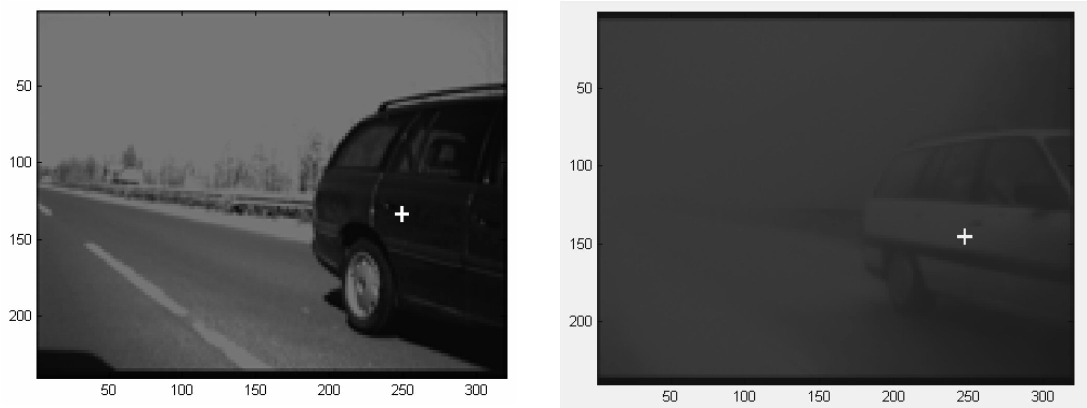

Fig. 6. Car position estimation results are marked using a white cross. We show the result of car position estimation in two different sequences. The left column (a) are the results of a black car in a shinny day recorded using a conventional CCD camera. The frames on the right (b) show the position of a white car recorded using a high dynamic range camera in a foggy and rainy day.

One important consideration is that this processing step is independent of the optical flow algorithm used. Therefore, we can use other algorithms such as those evaluated by Barron (1992). Betters results will be found using algorithms that provide very uniform optical flow results, such us the one we presented here.

4. CONCLUSIONS

We present a system to track the overtaking car using the rear-view mirror perspective. Basically, we use two steps, first we compute the optical flow using a strongly bio-inspired system that gives us a robust method of estimating the motion cues. The second step generates a saliency map that represents reliable car points that are used to compute the overtaking car position.

The results shown are very promising, because the system is very robust and stable, even for very difficult image sequences with bad visibility conditions. As the future work we plan to test the proposed scheme in presence of multiple car sequences.

5. ACKNOWLEDGEMENTS

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