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VIDEO PROCESSING ALGORITHMS FOR ROBOT MANIPULATOR VISUAL SERVING

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У статті зроблений акцент на сучасну світову тенденцію роботобудівництві . Показані основні галузі застосування роботів, та зазначено загальний недолік, що вадить подальшому динамічному розвитку галузі. Розглянуті підходи до реалізації зворотнього зв'язку порівняно робота методів обробки відеосигналу за алгоритмами Хорна - Шунка і Лукаса - Канадє з метою реалізації зворотнього зв'язку за візіо інформацією у задачах керування роботом у режимі реального часу

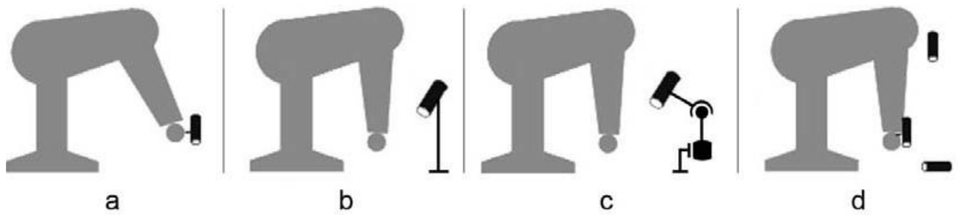
Introduction. The robotics industry is dynamically evolving after the worldwide economic and financial crisis. According to statistics [1] in 2010 took place almost a double increase in sales of robots in the market compared to 2009. It is about 118 thousand units of industrial robots and 2,2 million service robots for private and domestic use. This tendency continues to grow as it predicted in [1], even so the robots are excluded from many application areas where the work environment and object placement cannot be accurately controlled. And the reconstructions of our world to suit the robots obviously would not be cost effective. This drawback for robots is due to numerous reasons. These include a lack of sensory capability, their mechanical design, and deficient motion control. Robots will only suit the environment which is built for humans if they have almost the same size as humans and the motion/perception capabilities are similar to humans.

A (mobile) manipulator which is controlled by vision is an attempt to imitate a human abilities. To use vision as a sensor is cost effeective and very powerful in receiving information from the environment.

Main. The using of video information for develop the perception capabilities of robots has been one of the main research issues for more than three decades, this approach to control a robot is commonly termed visual serving [2]. Select the location of cameras is not unique, in Figure 1 shows some of the approaches taken.

There are two fundamentally different approaches to visual servo control: Position- Based Visual Servo (PBVS) and Image-Based Visual Servo (IBVS). Position-based visual servoing, shown in Fig. 1a, uses observed visual features, a calibrated camera and a known geometric model of the target to determine the pose of the target with respect to the camera. Image-based visual servoing, shown in Fig. 1b,c, omits the pose estimation step, and uses the image features directly [2].

In practice there are the monocular cameras, the binocular (for stereo imaging) cameras and conventional perspective cameras (for catadioptric imaging) can be used.



Fugure 1 - Camera-robot configurations: a) monocular eye b) monocular c) monocular with pan-tilt d) redundant camera system

From visual information we can deduce the size, shape and position of objects around the robot as well as other characteristics such as color and texture. This knowledge about the world can expand the range of tasks from the industrial to the social. In industry vision applied for recognition of variety of complex industrial parts, based on the previously learned [3, 4], optimal sequence of robot configurations that enable a precise point-allocating task applicable, for instance, to spot-welding, drilling, or electronic component placement maneuvers [5], tracking the moving target along own trajectory and as results in interception and grabbing of the target object [6]. The robot can be an assistant when performing everyday tasks at home, interacting with a person or group of people, interacting with a pet in human absence [7..10].

The a large number of artificial cognitive system comprise of vision, communication and manipulation subsystems, which provide visual input, enable verbal and non-verbal communication with a tutor and allow interaction with a given scene [11…16].

Various sources that provide information about optical flow, tend to give their definition of the object. Here are some of them: optical-flow pattern is the apparent motion of objects, surfaces or edges of the scene, the resulting movement of the observer (eye or camera) on the scene [17]; optical-flow - the movement of individual pixel video sequence. But for the mathematical description of the optical flow we consider the notion of a vector field.

The vector field is a two-dimensional matrix of two-component vectors. They can be used to convert images in which each vector represents the direction and intensity of the local geometric deformation. The elements of a vector field can be represented as a kind of character assignment statements: in each case, the role of the variable is a variable pixel located at the beginning of the vector and sets its value is the color of a fragment of the original image, which indicates a vector opposite to this.

Optical flow between a pair of images is a vector field that specifies a natural (in the broadest sense) transformation of the first image in the second.

The equation for the pixel (x, y, t) with the intensity I of a two-dimensional optical flow can be [18]:

$$I(x,y,t) = I(x+\delta x, y+\delta y, t+\delta t)$$

Given that the movement are small, using a Taylor series:

$$I(x+\delta x, y+\delta y, t+\delta t) \approx I(x,y,t) + \frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial t}\delta t$$

From these equations it follows:

$$\frac{\partial I}{\partial x}\delta x + \frac{\partial I}{\partial y}\delta y + \frac{\partial I}{\partial t}\delta t = 0$$

or

$$\frac{\partial I}{\partial x}\frac{\delta x}{\delta t} + \frac{\partial I}{\partial y}\frac{\delta y}{\delta t} + \frac{\partial I}{\partial t}\frac{\delta t}{\delta t} = 0$$

As a result, we obtain:

$$\frac{\partial I}{\partial x}V_x + \frac{\partial I}{\partial y}V_y + \frac{\partial I}{\partial t} = 0$$

V_x , V_y - rate of change of optical flow on the relevant coordinates.

$\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}, \frac{\partial I}{\partial t}$ - derivatives of the image.

There are two main algorithms for the determination of optical flow. The algorithm of Horn - Schunck suggests smooth flow around the image. Thus, he tries to minimize the distortion in the flow and the solution is to impose greater smoothness. The drawback of the algorithm is sufficiently large noise due to the high flux density. The algorithm of Lucas - Canada based on the assumption that the local neighborhood of each pixel value of optical flow the same way, so we can write the basic equation of optical flow for all pixels in the neighborhood and solve the resulting system of equations by the method of least squares.

This algorithm is less sensitive to noise in the images than the pointwise methods, however, is purely local and cannot determine the direction of the pixels within the homogeneous regions.

In an environment Matlab\Simulink implemented tracking and processing of optical flow for both algorithms, as described above.

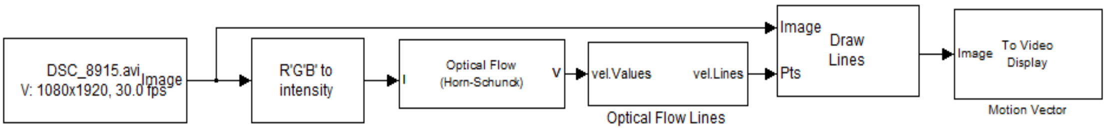


Figure 2 - Example of a program to determine the optical flow in the environment of Matlab\Simulink

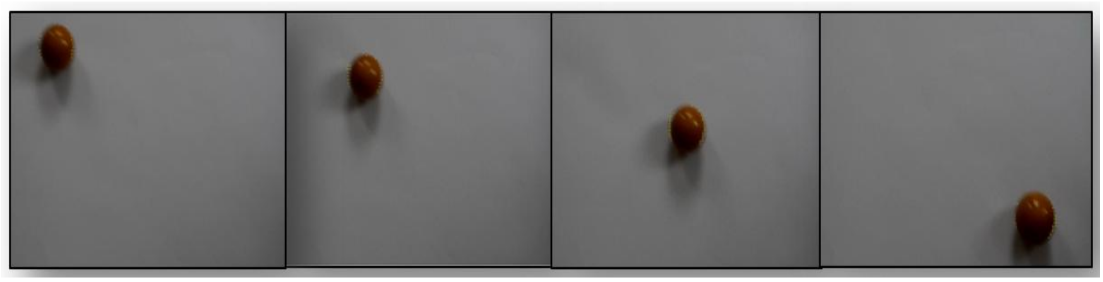
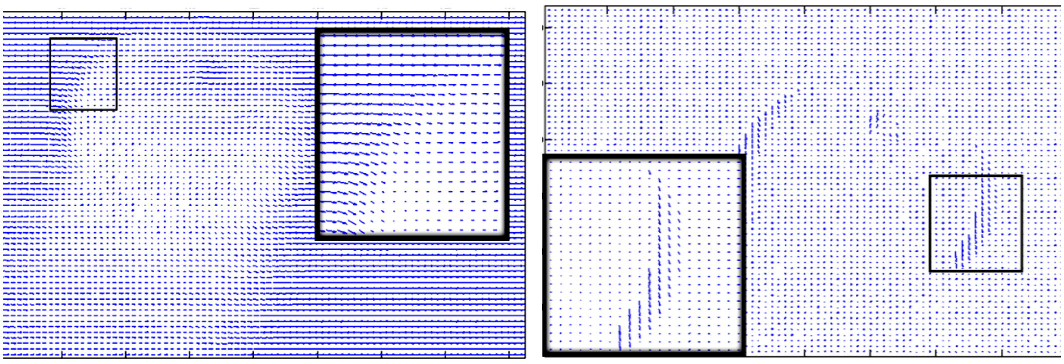


Figure 3 - Interpolation between frames in finding the optical flow



a) b)

Figure 4 - Vector field and optical flow a) algorithm for the Horn-Schunk; b) algorithm Lucas-Canada

Conclusion: as can be seen from the images the Horn-Schunck algorithm gives more accurate optical flow field. These differences are related to the principle of operation of both algorithms (Horn-Schunck - point, Lucas, Canada - local). As a consequence, the Horn-Schunck method is more accurate, and the method of Lucas-Canada, has a better performance. Both algorithms are implemented and used in robotics. This direction is being actively developed in many laboratories around the world

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