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COMPARISON OF TRACKING METHODS IN RESPECT OF AUTOMATION OF AN ANIMAL BEHAVIORAL TEST

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Abstract

Automation in experiments carried out on animals is getting more and more important in research. Computers take over laborious and time-consuming activities like recording and analysing images of the experiment scene. The first step in an image analysis is finding and distinguishing between the observed animals and then tracking all objects during the experiment. In this paper four tracking methods are presented. Quantitative and qualitative figures of merit are applied to confront those methods. The comparison takes into consideration the level of correct object recognition during different disturbances, the speed of computation, requirements as to the frame rate and image illumination, quality of recovering from occluded situations and others.

Keywords: analysis, object tracking, animal social interaction tests

1. Introduction

A great number of biological and medical experiments carried out on animals are now being automated. There is a great number of commercial systems that offer recording, analyzing and elaboration of results of experiments. Most commonly, the subjects of studies of those systems are animals' motor and activity functions. Parameters such as velocity, time of activity or time spent in a defined area are measured. Although the availability of such kind of systems is constantly growing, there are still no tools for automatic analysis of animals' behavior. The reason for this lies in the complexity of a living organism's behavior, in the difficulty in defining features of specific action and recording all details needed on a computer.

In advanced analysis, the first obstacle to overcome is finding and discerning the objects. Next, tracking the position of recognized individuals in consecutive video frames is needed. To facilitate these operations some conditions like motionless and contrastive background or different colors of objects can be required. However, situations that cause problems in computer analysis are inevitable. One of those situations is the contact of two or more individuals in the case of fight, sniffing or biting. It is problematic for computer application to distinguish between bodies of each connected object and to track each individual after separation. Sometimes one object is covered by another which brings the next problem: tracking an object that is not directly visible.

In this paper a review of some of the most popular tracking algorithms is shown. The choice of described algorithms was imposed by the degree of usefulness or meeting the assumptions of a specific method (for example: linear and Gaussian model in Kalman filtering) from algorithms not requiring earlier supervised learning presented in [1]. Methods based on shape or silhouette matching were not under consideration by reason of a large variation of rats' body shapes. Also algorithms that operate on texture were rejected due to too low image resolution.

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Testing was carried out on the recordings from a social interactions test of two male rats performed in the Department of Animal Physiology at the University of Gdansk. The description of a kind of social interaction test can be found in section 2.1. All presented methods are described in section 2.2. Each of them is tested and marked according to eight parameters described in section 2.3. Section 3. contains the results of experiments. A discussion is presented in section 4 and conclusions are contained in section 5.

2. Materials and Methods

2.1. Social Interaction Tests

Social interaction tests are often required before various medical and biological experiments conducted on rodents. Their aim is to determine the level of the domination and social status of each specimen in the group. Tests made for the purpose of the experiment described in this article were carried out on the basis of the Albonetti and Farabollini method [2]. This method discerns four types of behaviour: aggressive, defensive, ambivalent and neutral. The aggressiveness factor is computed on the basis of the number of behaviors from each category observed during 15 minutes of the test. Animals were tested in pairs in the round robin system. All specimens were males of the same age. To differentiate the tested individuals, one of them was painted red. The animals were put in a cage made of plexiglass and recorded by a camcorder situated above. All of them were earlier accustomed to the cage one by one.

The IqinVision IQEye 705 network camcorder was used for recording. In order to provide an easy separation of the objects of interest, the background was dark to form a contrast with the white rats. Two different frame rates (10 and 30 frames per second) and three different levels of lighting (poor, medium and strong) were used during recordings. The picture definition was set to 320x240 or 640x480 pixels.

2.2. Tracking Algorithms

The first step of an automatic analysis of animals' behavior is isolation of the object of interest from a frame of the recording. The high color contrast between the animal and the background enables the simplest object detection method - thresholding. The color space of the picture is changed into two colors (most often black and white) according to the specified level of the threshold. The object is marked with one color while the background with the other. Another method to detect the animal is a subtraction of the recorded frame from a reference image (image of the background), which results in detecting differences between these two images. The object found in the image should be then tracked through all frames of the recording.

Tracking is much more complex than detection. There are several popular methods concerning tracking.

2.2.1. Continously Adaptive Mean-Shift

The Continously Adaptive Mean-Shift (CamShift) is built on the Mean Shift method [3, 4]. The Mean Shift algorithm is a method of finding local extrema in the density distribution of a data set and shifting the fixed window according to the computed centre of gravity. Each video frame is converted to a color probability distribution image of a tracked color histogram model.

The algorithm runs as follows [5]:

a. Choose a search window:

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– its initial location;
– its type (uniform, polynomial, exponential or Gaussian);
– its shape;
– its size.

b. Compute the window's (possibly weighted) centre of mass.
c. Centre the window at the centre of mass.
d. Return to step b) until the window stops moving (according to the maximum number of iterations or epsilon change in the centre shift between iterations).

Fig. 1 shows a schema of the described algorithm. The frame on the left displays an image with window centred in the centre of mass. A movement of the object causes a shift of the centre of mass and respectively of the window.

Bradski [6] introduced CamShift to track the human face based on the skin color. It differs from the Mean Shift in adjusting the search window in size, which allows for the tracking of objects whose size may change during the video sequence.

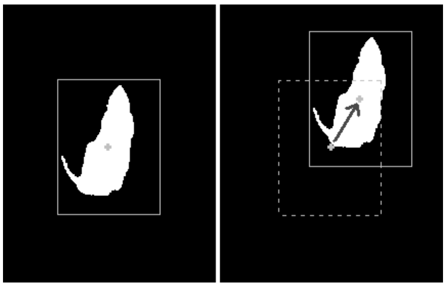

Fig. 1. A schema of the Mean Shift algorithm.

2.2.2. Optical Flow

The Optical Flow (OF) is a vector field that describes changes of one frame comparing it to another in a sequence of images (Fig. 2). This method determined in [7, 8] tracks each pixel according to its brightness through successive frames by defining the vector of displacement between individual images.

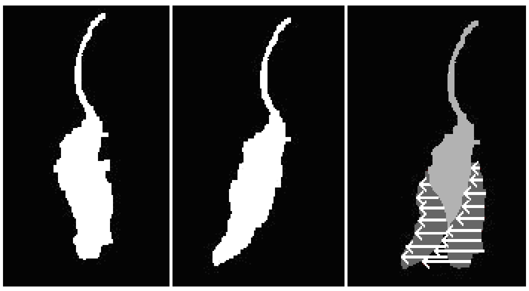

Fig. 2. An example of creating an OF image from two images determining a movement.

Let the image brightness at the point *(x, y)* in the image plane at time *t* be denoted by *I(x,y,t)*.

The algorithm assumes that:

a. The brightness of every point of a moving or static object does not change in time
$I(x+dx, y+dy, t+dt) = I(x, y, t)$
b. The velocity of brightness varies smoothly in a greater part of the image. In practice, this means the temporal increments are small relative to the frame rate, motions are small from frame to frame.

c. Neighboring points in a scene belong to the same surface and have a similar motion. The OF method can be used only for objects of a finite size undergoing motion or deformation. There is little hope of recovering the velocities of small points.

The first assumption demands stable lighting. The second assumption imposes a requirement on the camera frequency of capturing frames.

2.2.3. Particle Filtering

Particle filtering (PF) (also often called Condensational algorithm) was developed to track cluttered objects and has been described in literature [9, 10]. In general, it is a sequential Monte Carlo method based on point mass representations of probability densities (particles). The basic idea is the recursive computation of relevant probability distributions describing the object's configuration using the importance sampling and approximation of probability distributions with discrete random measures.

The PF algorithm works iteratively as follows [11]:

a. Initialize the particles and compute their likelihood distribution.
b. Sample the current set of particles to generate a new particle set using the sampling algorithm.
c. Given the new observation, generate the new sample set by applying the transition function and update the weight of each particle.

A common problem with the conventional algorithm of PF is the degeneracy phenomenon, where after a few iterations, all but one particle will have negligible weight. This has been tried to be solved by replacing Sequential Importance Sampling (SIS) [12] by other methods such as the Sampling Importance Resampling (SIR) [13], the Auxiliary Sampling Importance Resampling (ASIR) [14], the Regularized Particle Filter (RPF) [15] or the Mean Shift [16].

The Mean Shift Embedded Particle Filtering combines the PF and the Mean Shift algorithms (precisely CamShift) [16]. The Mean Shift iteration based on observation of density is applied to all samples after those samples were measured by observation. As a result, each sample will converge to a nearby local mode of observation distribution. Many of them will gather in the same local maximum, so the mean shift embedded into particle filtering can use fewer samples than other particle filtering algorithms. Another advantage is adaptability of the color model of the tracked object to deal with color variation.

2.2.4. Active Contours

The Active Contours algorithm (AC), also called "snakes", was introduced in [17] as an energy-minimizing spline guided by external constraint forces and influenced by image forces that pull it toward features such as lines and edges. Energy of active contours is the sum of: internal energy of the spline due to bending, image energy caused by the image forces (attracting the snake to lines, edges and terminations) and energy of additional constraints caused by the external constraint forces. The aim of the AC is to find a location that minimizes energy. Snakes are able to find edges with ease by attracting the spline to the largest image gradients. Once a snake finds a desired feature, it tracks it during its motion by tracing the same local minimum.

2.3. Parameters

In order to draw a comparison between the above-mentioned tracking methods, eight parameters were elaborated:

a. Optimal light conditions – the level of light appropriate for the best tracking by each algorithm. The choice is made from among three kinds of light (Fig. 3):

– poor, overhead,
– medium, diffuse, overhead and side,
– strong, point-source, side and overhead.

a) b) c)

Fig. 3. Examples of levels of light: a) poor, b) medium, c) strong.

b. Average time of analyzing one frame – average operating time of an algorithm for one frame of a movie of 320 pixels width and 240 pixels height, written as the avi file. It is measured in milliseconds. The calculations were carried out by a computer with an Intel Pentium 5 procesor, 2.80 GHz and 1,00 GB RAM.
c. Initial (input) parameters – the parameters necessary to be entered by the user for analysis initiation.
d. Resultant (output) parameters – the parameters received as a result of analysis, the way of presenting the outcome of tracking.
e. Conformity of tracking under different frame rate conditions – the deviation of tracking a fixed object in recordings (parameters of tracking are normalized to a maximal value) with different frame rates computed according to (1)

$$conf_{fr}[\%] = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{conf} - \mu)^2} \tag{1}$$

where: μ – mean value of the parameter, N – number of observations,
x_{conf} – normalized values of evaluated parameters in each movie calculated from (2)

$$x_{conf}[\%] = \frac{x_i}{\max_{val}} * 100\% \tag{2}$$

where max_{val} – maximal value of the evaluated parameter (320 for x-coordinate or width and 240 for y-coordinate or height), x_i – subsequent values of the evaluated parameter in each recording.

The estimation of tracking conformity under different frame rate conditions was carried out on the identical recordings of different frame rates (30, 15, 10, 5 and 2.5 fps). The recording lasted 50 seconds (30 fps), was poorly lighted and showed one white and one painted red rat.

Each algorithm had different parameters describing tracking:

– Camshift – x- and y-coordinate of the centre of the tracked box (area), width and height of the tracked box, all parameters counted separately for the selection of the red and white rat,
– Optical flow – x and y position of tracked points, parameters counted for two points (one situated on the white and one on the red rat),
– Particle filtering – x- and y-coordinate of the centre of the tracked area, width and height of the tracked area,
– Active contours – x and y position of the centre point of the contour, size of each contour.

f. The quality of tracking during light changes – reaction for light changes defined on the basis of observation of tracking objects by each algorithm using the recording of 10 frames per second, 320x240 pixels containing smooth light enhancement. Fig. 4 shows the changes of the mean value of all pixels in the grey scale during light enhancement and back to the initial lighting level.

Fig. 4. Mean value of pixels in recording containing light changes

g. Tracking analysis during disturbances – a proportional analysis of recording containing three types of disturbances:
- an extraneously large object in the field of interest – the hand of the researcher putting the second rat into the cage;
- an extraneously small object beyond the field of interest – the hand of the researcher moving the computer mouse;
- changes of all pixel values, additional reflections – a sheet of glass pulled over the cage to cover it.

The analysis contains such parameters as:
- Atc – the percentage of the total time spent on correct tracking,
- Atp – the percentage of the total time spent on partly proper tracking – tracking only a part of the object, tracking more than the object (background, another rat),
- Ad_1c, Ad_2c, Ad_3c – the percentage of the disturbance (respectively: large object, small object, pixel changes) time spent on correct tracking,
- Ad_1p, Ad_2p, Ad_3p – the percentage of the disturbance time spent on partly proper tracking.

The computations were made using the poor lighted movie lasting 20 seconds of 10 fps frequency and 320x240 pixel resolution. The duration of each disturbance:
- the extraneously large object in the field of analysis – 5.75% of the total time of recording,
- the extraneously small object beyond the field of analysis – 7.35%,
- the changes of all pixel values – 13.9%.

h. Time and degree of recovering from occlusion – the time of retrace of tracking the red rat after covering it by the white rat to the completely correct identification (counted from the first frame of the side exposure) and the time to the first correct object detection, the percentage of the body part correctly recognized in the first correct detection after uncover. The exemplary incident of objects imposition lasted 6.73s and had five stages (Fig. 5): snout contact – 0.2s, head covering – 1.83s, complete covering (except tail) – 0.4s, side exposure – 0.3s, side contact – 4s.

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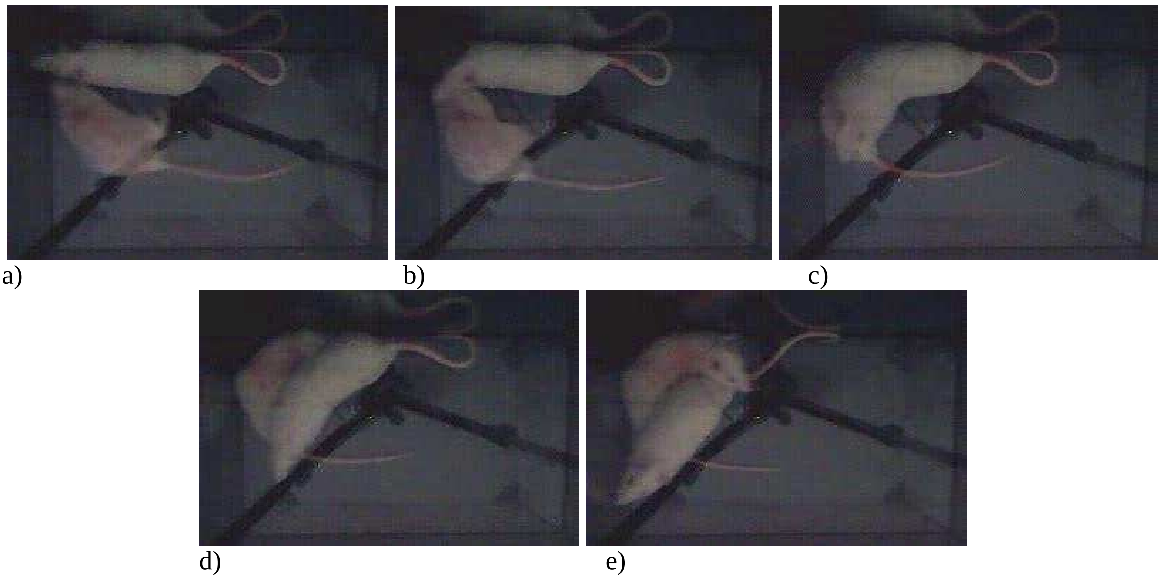

Fig. 5. Stages of covering: a) snout contact , b) head covering, c) complete covering, d) side exposure, e) side contact

The observation was carried out on a recording with the following parameters: 30 fps, resolution of 320x240 pixels and poor light.

3. Results

3.1. Optimal light conditions

Table 1 describes the quality of tracking under different light intensity for all methods. The best results of tracking were obtained for the poor light, largely due to lack of reflections which cause misidentification. Low quality of tracking by the OF in the strong and medium light is also induced by the irritability and restlessness of rats in the light environment (they move more quickly and thus break one of the optical flow assumptions), that is characteristic of all rodents. Tracking by the CamShift and the PF in the poor and medium light gives similar, satisfactory results; strong light disturbs proper identification. AC analysis strongly depends on the image brightness, only in poor light it works correctly.

Table 1. The quality of tracking under different light intensity for all algorithms

	CamShift	OF	PF	AC
poor light	No reflections, very small difference in brightness between the objects and background	The point situated on the white rat was migrating from one rat to the other during body contact	Finds the objects correctly	Works correctly
medium light	Too bright light causes reflections of objects in the side glass pane which are very rarely mistaken with the object itself.	The point was migrating to the other rat, reflections and the background	Finds the objects quite well	Red rat is darker than the background
strong light	More reflections more often acclaimed as part of the object	The point was migrating to the other rat, reflections and the background	Light background, noisy image	Very light background, noisy image

3.2. Average time of analyzing one frame

The average operating time for each algorithm is shown in Table 2.

Table 2. An average time of analyzing one frame by each algorithm

	CamShift	OF		PF		AC
		20 points	400 points	1 object	2 objects	
Average time of analysing one frame [ms]	38	51	424	499	1497	609

For the OF the results depend on the number of tracked points: the more points are to track, the longer the time of analysis. A similar case can be observed for the PF. Two objects of interest demand more time for operating (1497 ms) than one object (499 ms).

The results indicate that the CamShift algorithm is the quickest way to track a rodent in the cage (38 ms). The OF for a small number of points is also fast (51 ms – 20 points). A greater number of the tracked points (400) increases the time of analysis to 424 ms, which is comparable to tracking one object by the PF (499 ms). The AC algorithm requires 609 ms to analyze one frame of the recording. The most time-consuming method is the PF for two objects (1497 ms).

3.3. Initial parameters

The OF and CamShift algorithms require respectively the initial points and initial area (Table 3). Particle filtering and active contours do not need any initial parameters.

3.4. Resultant parameters

All the resultant parameters are shown in Table 3. The results of the CamShift and the PF algorithms are given in the form of an area: centre point, width and height of the tracked region (box). The OF produces as a result the position of the tracked points, whereas the AC evaluates the position of each point for each contour.

Table 3. Initial and resultant parameters for all algorithms

	CamShift	OF	PF	AC
Initial parameters	area	point / points	-	-
Resultant parameters	area	point / points	area	points of contours

3.5. Conformity of tracking under different frame rate conditions

a) CamShift

Table 4 demonstrates the results of tracking the centre of an object under different frame rates for the CamShift. The coordinates of the centre of the tracked area are very similar for all values of the frame rates ($conf_{fr}$ = 3.13% and 2.92% for the white rat and 3.81% and 2.08% for the red rat). Fig. 6 displays the values of pixels (in grey scale) of an x- and y-coordinate of tracking the box centre and the width and height of the tracking box under different frame rate conditions by the CamShift for the red rat. Only the 2.5 and 15 frames per second frequency occasionally diverges from other frequencies in tracking the centre point of the box (Fig. 6a, b). The width of a tracked area varies the most ($conf_{fr}$ = 19.55% for the white rat and 12.49% for the red rat). Values of the width for 2.5 fps are visibly greater than other results (Fig. 6c). The diversity of height of a tracked object is at a middle level (8.02% - the

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white rat, 4.3% - the red rat) when comparing with other values. Though, Fig. 6d shows a significant difference between the results for 2.5 fps and others.

Table 4. Conformity of tracking under different frame rate conditions for the CamShift

Camshift	$Conf_{fr}$ of x-coordinate of area centre [%]	$Conf_{fr}$ of y-coordinate of area centre [%]	$Conf_{fr}$ of width of area [%]	$Conf_{fr}$ of height of area [%]
white rat	3.13	2.92	19.55	8.02
red rat	3.81	2.08	12.49	4.3

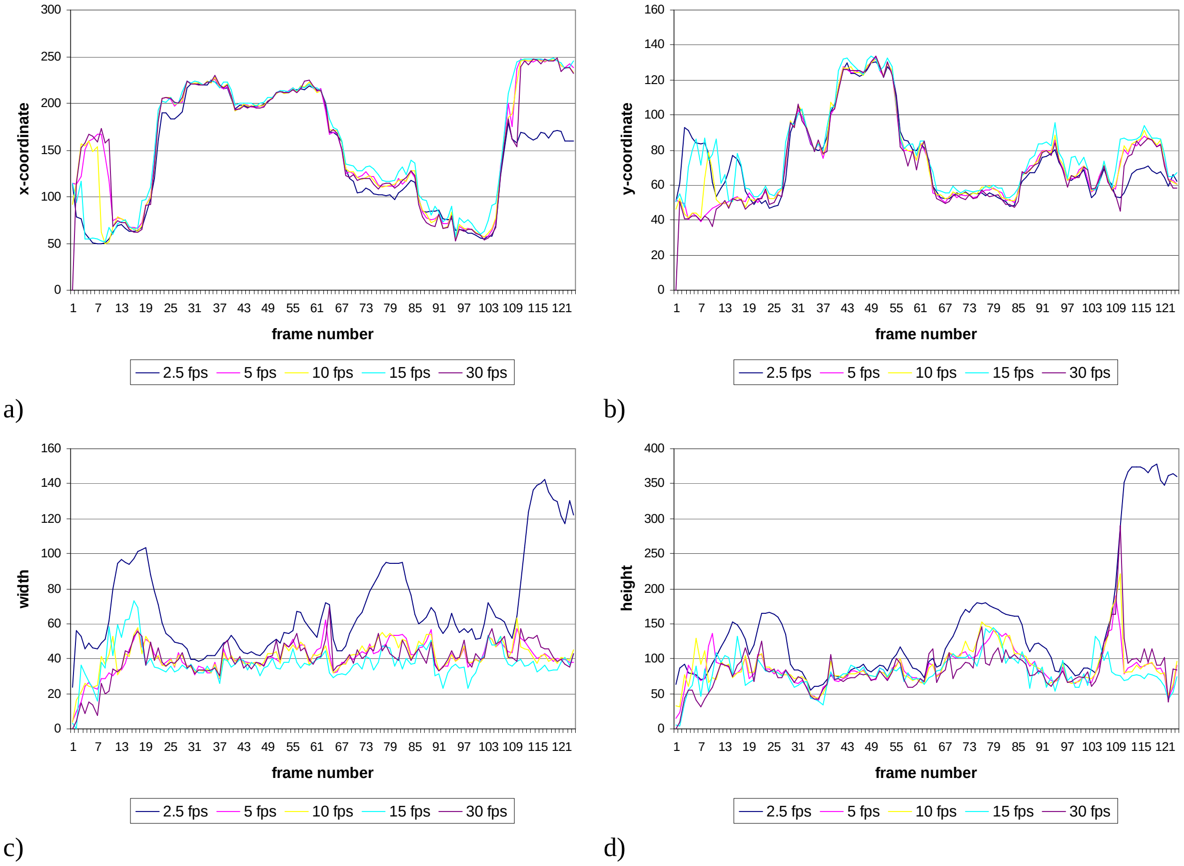

Fig. 6. Pixel values of a) x-coordinate of the tracking box centre, b) y-coordinate of the tracking box centre, c) width of the tracking box, d) height of the tracking box under different frame rate conditions for the red rat by the CamShift.

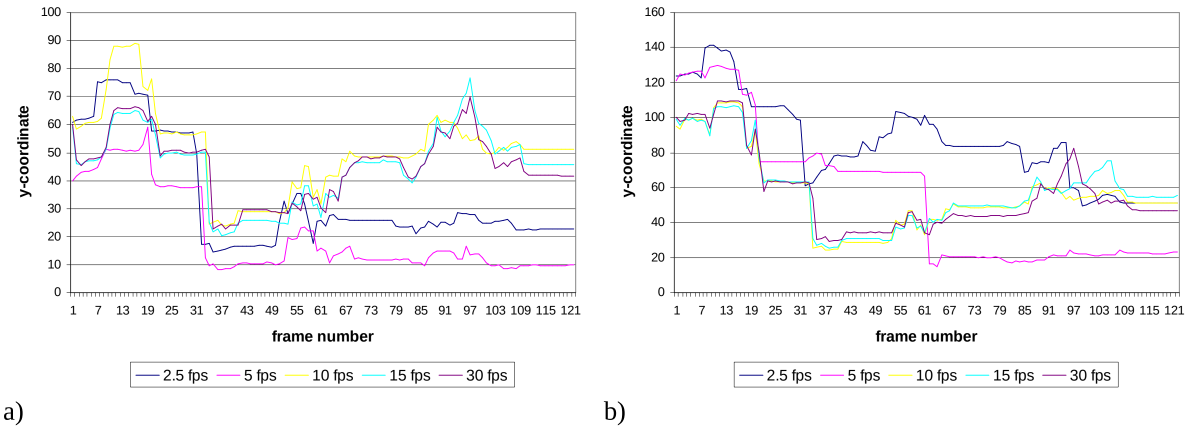

Fig. 7. Pixel values of y-coordinate of the tracked point under different frame rate conditions for the a) white and b) red rat by the OF

b) Optical Flow

The conformity of tracking under different frame rate conditions for the OF is between 5.68% and 8.85% (Table 5). The results are not as even as those achieved by the CamShift. Therefore, it is hard to find frequencies that significantly differ from others. Only the y-coordinates of 2.5 and 5 fps draw a shape distinction (Fig. 7).

Table 5. Conformity of tracking under different frame rate conditions for the OF.

OF	$Conf_{fr}$ of x-coordinate of point [%]	$Conf_{fr}$ of y-coordinate of point [%]
white rat	7.35	5.68
red rat	8.85	8.23

c) Particle Filtering

Particle filtering revealed the worst abilities in similarity of tracking through all the measured frame rates. The conformity of tracking the area of the centre equals from 14.34% to 31.52%, and that of the dimensions of the area is from 12.16% to 14.49%. Such poor results are in part caused by prediction of the next frame in the PF algorithm. After changing the frame rate, the prediction is also changed.

Table 6. Conformity of tracking under different frame rate conditions for the PF

PF	$Conf_{fr}$ of x-coordinate of area centre [%]	$Conf_{fr}$ of y-coordinate of area centre [%]	$Conf_{fr}$ of width of area [%]	$Conf_{fr}$ of height of area [%]
White rat	31.52	20.34	13.72	14.49
Red rat	25.7	14.34	12.16	14.4

d) Active contours

The AC is the most unresponsive to the frame rate changes algorithm. The conformity of tracking the contour centre is below 1% (0.97% for the x-coordinate and 0.62% for the y-coordinate, Table 7) and tracking the size of contour comes to 2.99%. Fig. 8 demonstrates plots of the contour size for all frequencies of the frame rate. It can be observed that all values are almost identical for most of time. There are only two cases where the results diverged (Fig. 8). The first one arose due to a sudden increase of the contour size for 2.5 fps, a moment later a similar rise appeared for 2.5, 5 and 10 fps. Relatively small changes of the contour size can be caused by stretching or cringing. A sudden high increase is often the result of integration of two separate objects.

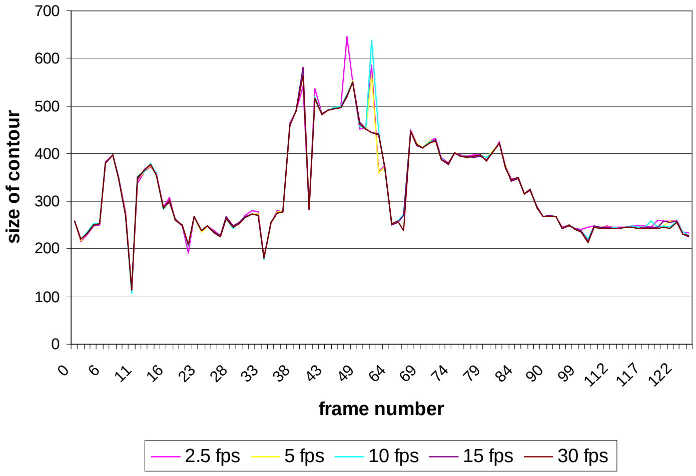

Fig. 8. The values of exemplary contour size under different frame rate conditions by the AC.

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Table 7. Conformity of tracking under different frame rate conditions for the AC.

AC	$Conf_{fr}$ of size of contour [%]	$Conf_{fr}$ of x-coordinate of contour centre [%]	$Conf_{fr}$ of y-coordinate of contour centre [%]
	2.99	0.97	0.62

3.6. Quality of tracking during light changes

Light changes have no impact on tracking by the CamShift (Table 8). The OF lost all the tracked points in one frame. The PF and the AC are working on binary images. This kind of image is most often acquired by performing a threshold at a fixed value, which is the reason why the PF and the AC are sensitive to changes of the light. The PF finds more objects whereas the active contours increase the number and enlarge the borders of contours.

Table 8. Influence of light changes on tracking by each algorithm

	CamShift	OF	PF	AC
Influence of light changes on tracking	No impact	Almost all of tracked point lost the objects in 420 frame	More objects detected during light phase of recording	More objects detected during light phase of recording

3.7. Analysis of tracking during disturbances

Table 9 demonstrates the results of analysis of recording containing disturbances featured in section 2.3., subsection g) .

From among all the tracking algorithms, the CamShift is the most accurate (91.37% of correct and 4.79% of partly correct tracking in general). A small object located near the field of interest does not disturb proper working (Ad_2c = 100%). Also putting the glass in front of the camcorder has a minor effect on computation correctness (79.31% of correct and 20.69% of partly correct tracking). Though, a large object located in the field of interest causes an incorrect tracking at the level of 66.66% which makes the CamShift the worst algorithm to work with large extraneous objects.

The OF did not manage to track the object all the time. The tracked point moved from the red rat to the white one during the body contact (passing by) and remained there for the rest of time. Two values for Atc and Atp stand for tracking the red and the white rat respectively (the percentage of the tracking time – about half of the total time). The OF algorithm is quite effective in general correct tracking (62.92% and 84.85%). However, after losing the tracked point it is hard to recover. A small disturbing object and pixel values changes have no impact on tracking (100% of correctness). A large disturbing object introduces errors in 27.78% of cases.

The PF has the lowest level of correctness (38.5%) but quite high partial recognition of the object (53.51%) in general. Tracking with a large disturbing object is of 50% of correctness and only 25% of failure. A low value of the properly analyzed recording with small disturbances (15.22%) is not a result of those disturbances but of the body contact of the two objects, which is proven by the high value of a partly proper analysis (84.78%). Also pixel value changes perturb correct working of the PF method (0% of correct and 100% of partly proper tracking).

According to the outcomes, the most resistive to large disturbing objects is the algorithm of the AC (72.22%). The insusceptibility to small disturbances is also at a high level (86.96%). However, pixel value change is a factor that has a great impact on tracking (0% of correct and 100% of partly proper tracking). A general level of tracking comes to 48.88% for the correct analysis and 47.44% of partially proper tracking.

Table 9. Values of parameters of analysis during disturbances for all algorithms

Parameters [%]	CamShift	OF	PF	AC
Atc	91.37	62.92 / 84.85	38.5	48.88
Atp	4.79	14.29 / 0	53.51	47.44
Ad_1c	16.67	0	50	72.22
Ad_2c	100	100	15.22	86.96
Ad_3c	79.31	100	0	0
Ad_1p	16.67	72.22	25	5.56
Ad_2p	0	0	84.78	13.04
Ad_3p	20.69	0	100	100

3.8. Time and grade of recovering from occlusion

Table 10 illustrates abilities to recover from occlusion for all the tracking methods. The CamShift demonstrates the best properties of object retrieval. It took 0.3s to find the whole body of the object. What is important, 0.3s is the time of side exposure, which means that the whole object was found by the CamShift in the first frame it appeared. The CamShift recovers in no time at all (0s is needed to find 50% of the object body – the stage of side exposure).

Completely different results were estimated for the OF. It lost the rat in the third phase of covering and never tracked it down again (all points of tracking moved to the white rat).

The PF and the AC have similar values of the discussed parameters. They fully recovered after almost 5 s. (4.97s – particle filtering and 4.5s – active contours) – after body separation, and found about a half of the object for the first time after 0.4s and 0.43s. – during the last phase of covering.

Table 10. Values of time and grade of recovering for all algorithms

		CamShift	OF	PF	AC
Time of recovering to completely correct tracking [s]		0.3	-	4.97	4.5
First correct object detection	Time of recovering to first correct object detection [s]	0	-	0.43	0.4
	Grade of recovering [%]	50	-	50	40

4. Discussion

This article presents the results of testing four tracking algorithms working under different conditions. Experiments were conducted with respect to an analysis of social interaction behavior of two rats.

The first test revealed that a poorly lighted image is much more easy to analyze than a lightsome one. Reflections of the objects in the glass walls cause more problems than dim images. Bright light had also an enormous influence on the rats behaviour. Rodents, nocturnal animals, perceive the lighted surrounding as a stressful environment and, therefore, act unnaturally. If there is a need to conduct experiments in bright light, non-reflective materials should be used for building the cage for animals.

The next analyzed feature was sensitivity to the captured frames frequency. Each algorithm was tested for five recordings of: 30, 15, 10, 5 and 2.5 frames per second. The more similar the results, the smaller the sensitivity and better multi-purpose usage. The most equal outcomes were achieved by the Active Contours. The value of the frame rate has no impact on working of this method. Also the algorithm of the CamShift is quite resistant to the different frames frequency, except the 2.5fps frequency. The lowest value seems not enough for tracking the objects by the CamShift, it sometimes differs from other results (especially in width and height of the tracked area). The divergence between the outcomes of a tracking

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point by the Optical Flow is greater than tracking the centre of the area by the CamShift (from 5.68% to 8.85%) but not as appreciable as one could suppose. A low frame rate of the recording is a failure to keep one of the optical flow assumptions. Decrementing the number of frames per second increases at the same time the motion between the two following frames. According to the condition for smooth variation of the brightness velocity of an image, the results of tracking should be very different for different frame rate values. A small difference between these results indicates that this condition is not essential for the concerned analysis or that the range of the frame rate values was incorrectly selected.

One of the tests demonstrated that the CamShift works invariably during the analysis of recording containing light changes. The Particle Filtering and the Active Contours operate on binary images for all frames achieved in the same way, which is the reason why those algorithms detect the change of the light. Adaptive threshold is one of the ways to solve this problem. The Optical Flow showed the worst properties, it lost all the tracked points at one moment. The explanation for this may be related to the appearance of the two parallel incidents: image highlighting and vigorous movement of the objects. Those two events are infringements of the optical flow assumptions: the brightness of each point does not change in time and the velocity of brightness varies smoothly.

Sometimes during recording of the experiment some disturbances of the recorded image appear. The CamShift seems to have the best general abilities to cope with aberrations. Though it lost the tracked area to the advantage of an extraneously large object, it recovered very fast, in contrast to the optical flow which permanently lost all the tracked points after the body-nose contact with another rat. The advantage of tracking by the Optical Flow is the lack of any influence on proper tracking while the disturbance is not close to the tracked point, and the low sensitivity to pixel value changes. The Particle Filtering and the Active Contours only partially identify objects correctly during pixel values changes, but quite well manage to distinguish large disturbance from the object of interest.

The last tests were made to verify the abilities of recovering from occlusion. The best results were again achieved by CamShift, it recovered just the time of the object reappearance. The Optical Flow did not manage to recover at all. The Particle Filtering and the Active Contours needed some time to recapture the object.

5. Conclusion

The research made for needs of this article can help in selecting the best tracking algorithm for specific experimentation. It also gives information about conditions that are the most suitable or which may disturb the operation by each method. Being aware of all the algorithms' weak points, a user can modify or combine the selected methods to adapt them to specific requirements.

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