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Modeling floor-cleaning coverage performances of some domestic mobile robots in a reduced scenario

T. Palleja, M. Tresanchez, M. Teixido, J. Palacin *

Department of Computer Science and Industrial Engineering, Universitat de Lleida, Jaume II, 69. 25001 Lleida, Spain

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ABSTRACT

In this paper, floor-cleaning coverage performances of some domestic mobile robots are measured, analyzed and modeled. Results obtained in a reduced scenario show that floor-cleaning coverage is complete in all cases if the path-planning exploration algorithm has some random dependence. Additionally, the evolution of the area cleaned by the mobile robot expressed in a distance domain has an exponential shape that can be modeled with a single exponential where the amplitude defines the maximum cleaning-coverage achieved and the time-constant defines the dynamic evolution of the coverage. Both parameters are robot dependent and can be estimated if the area of the room is known and then floor-cleaning coverage can be predicted and over-cleaning minimized.

1. Introduction

The repetitive and noncreative task of floor-cleaning is a clear application of mobile robots. Floor-cleaning can be identified as a complete-coverage problem where a given ground area has to be fully covered (cleaned) by a mobile robot. In the case of structured and/or known environments [1,2] this problem can be solved using one or multiple mobile robots [3] and a variety of methods as cellular decomposition [4] genetic algorithms [5,6], neural network approach [7,8], algorithms based in a exact cell decomposition [9], based on spanning trees [10], based on the execution of spiral filling paths [11–13], etc. Although, in most cases robot position must be known with great precision [14] and a real application of those algorithms in a mobile robot depends largely on the internal [15,16] and external [17–21] onboard sensors used for self location.

In the case of an unknown, unstructured and dynamic cleaning scenario, as the originated by the typical domestic decoration things and human disorder habits, the complete-coverage problem becomes more complex [2,9,22,23] and most commercial mobile robots use inefficient random path-planning algorithms [24] and very few inexpensive contact (or non-contact) collision sensors to get complete-coverage.

The main objective of this work is to model floor-cleaning coverage performances of some domestic random path-planning mobile robots through the measurement of its position and trajectory using an external vision system in a similar manner that is performed to identify kinematic parameters in robotic manipulators [25] instead of the typical self-localization problem [26,27]. Three commercial floor-cleaning mobile robots and one research prototype are measured, analyzed and modeled. RC 3000 Robocleaner, manufactured by Alfred Kärcher Vertriebs-GmbH, Postfach 800, D-71364 Winnenden, Germany; Trilobite, manufactured by Electrolux, S:t Göransgatan 143, SE-105 45 Stockholm, Sweden; Roomba, manufactured by iRobot, 8 Crosby Drive, Bedford, MA 01730, USA; and RoboNet an evolution of the research prototype presented in [24]. The commercial mobile robots selected were available in the market at the end of 2004 and currently all of them have an updated and improved version. Table 1 shows the image, the structural parameters and a simplified representation of the mobile robots including diameter and relative brush location. The simplified representation will be used to estimate the dynamic evolution of the cleaning-coverage from the trajectory of the mobile robot whereas the performances of its cleaning devices are not analyzed in this work.

The selected mobile robots use random straight path-planning in its control algorithm: going straight until collision and turning a random angle before going straight again. RC 3000 use a fully random path-planning control algorithm from the very beginning. Trilobite follows the perimeter of the room until some difficult path or the end of the perimeter is found and then changes to random path-planning. Roomba performs an spiral cleaning at the beginning that is very useful if the robot is placed in the center of an empty room but after collision the

* Corresponding author. Tel.: +34 973702724; fax: +34 973702702.
E-mail address: palacin@diei.udl.cat (J. Palacin).

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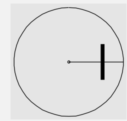
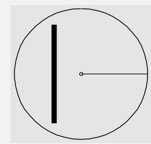
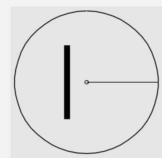
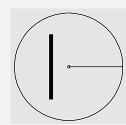
Table 1
Structural parameters of the selected mobile robots.

Robot	Image	Height (mm)	Diameter (mm)	Cleaning tool width (mm)	Representation	Main cleaning tool	Weight (kg)
RC 3000		105	290	95		brush	2.2
Trilobite		130	345	260		brush	5
Roomba		90	350	170		brush	2.7
RoboNet		110	280	212		brush	2

control algorithm performs some wall following and random path-planning exploration before repeating the spiral cleaning. RoboNet is fully based on a random path-planning control algorithm. RC 3000 uses mechanical sensors to detect collisions; Trilobite uses ultrasonic sensors for wall following and collision avoidance; Roomba uses mechanical sensors to detect collisions and one infrared sensor for wall following; RoboNet detects collisions with a two axis silicon accelerometer and supervising the speed and power applied to the wheels. In a preliminary work [24], the shape of the dynamic evolution of the total area cleaned by RoboNet was represented using different exponential models. In [28] the performances and total floor-coverage evolution obtained with two unspecified mobile robots were also measured obtaining a similar exponential evolution but no additional coverage modeling was performed. In this work, a single exponential model will be applied to estimate the dynamic cleaning-coverage evolution of all selected cleaning mobile robots.

The outline of this work is as follows: first, Section 2 describes the measurement system used to estimate trajectory and floor-cleaning evolution for the selected mobile robots. Section 3 presents the method used to model the evolution of the floor-cleaning coverage. Finally, Section 4 presents the conclusions.

2. Measurement system

A vision based measurement system first presented in [24] was developed to record and estimate the trajectory and cleaning-coverage evolution of the selected mobile robots. The measurement system has four main parts: the image acquisition device, the cleaning scenario, the image acquisition procedure, and the image analysis.

The image acquisition device is a CCD color camera with an internal Bayer filter and lens with a horizontal and vertical vision angle of 43° and 33° respectively. The camera is oriented perpendicular to the ground and located close to the ceiling of the laboratory and hold by a parallelepiped tubular aluminum structure. The standard USB interface is used to plug the camera to a PC for continuous image acquisition with a maximum frame rate of 30 fps although this value must be minimized depending on the speed of the robot and the image resolution to obtain the smaller file size in large captures. Image acquisition is started manually and no special trigger is needed to synchronize image acquisition with mobile robot movement.

The cleaning scenario is a selected rectangular floor surface limited by small wood walls (300 mm high) supported by a tubular rectangular aluminum structure attached to the ground. The walls are white for easy discrimination with the dark tile-floor of the laboratory; additional black or white objects can be also included to evaluate its effect in the cleaning process. The cleaning scenario was uniformly illuminated using standard fluorescents pointed to the white floor of the laboratory to obtain a diffuse illumination effect and avoid tile reflections. The combination of the height of the laboratory and camera lens has limited the scenario size to 1850×1355 mm (2.506 m^2) (Fig. 2-left) with an image resolution of 0.3 and 0.6 mm/pixel in VGA and QVGA formats.

Image acquisition procedure is based on three steps. In the first step a reference ground image of the cleaning scenario without the mobile robot is acquired and stored in the record file. In the second step the cleaning mobile robot covered with some reference marks is placed in the cleaning scenario in the desired position and orientation. In the third step continuous image acquisition and recording must be started while switching on the mobile robot. As an effort to reduce the size of the resulting file, all images acquired are converted into an indexed format with a color-map of 256 triplets of [R,G,B] color values, coding each image pixel with 8 bits. The common color-map of the recording is obtained from the first motion image to guarantee the inclusions of the original colors of the mobile robot.

Using indexed images the length of the resulting file is 3 times smaller without appreciable loose in quality because the texture of the ground is very repetitive in the entire cleaning scenario. Another advantage of this coding format is that individual image frames can be read asynchronously without having to decode part or the complete file. However, the main disadvantage is that the recording file is not compatible with standard multimedia players.

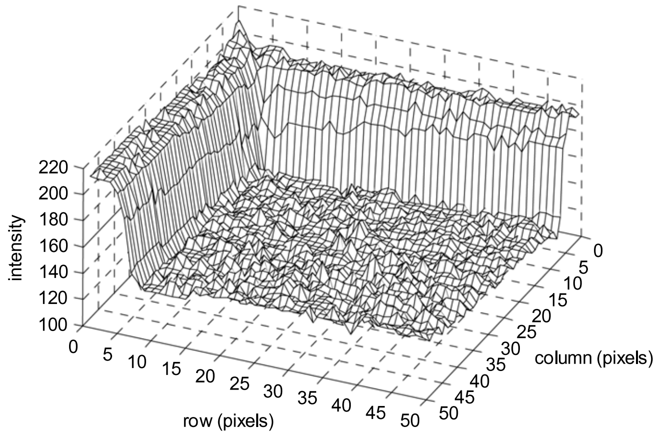


Fig. 1. Mesh representation of the gray-level values in one corner of one reference (or ground) frame: the white walls corresponds to he highest intensity and the dark floor to the lowest.

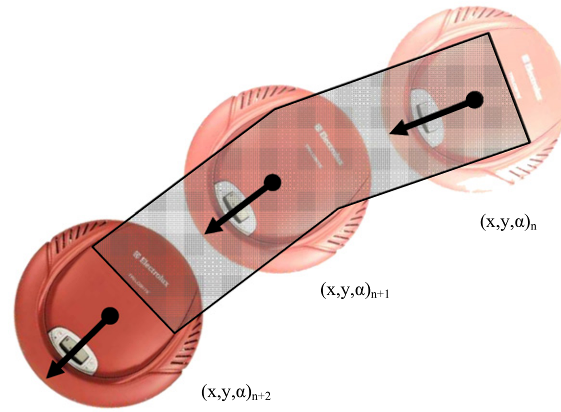


Fig. 3. Illustration example of the polygonal structure (dark filled) used to estimate the area covered by the cleaning device form the mobile robot coordinates (x, y, α) obtained in frames $\{n, n+1, n+2\}$.

In future measurement procedures and effort will be made in this direction to simplify the visualization of the recorded file.

Image analysis starts with the initial reference ground frame (without the mobile robot) to locate automatically the walls, other objects and to estimate the horizontal and vertical scale of the image. The height of the additional objects is limited to 100 mm to avoid mobile robot occlusion so, at this moment, chairs, tables, desks and other objects requires an initial manipulation or ground modeling to be included properly in the cleaning scenario. The contour of the wall is located through segmentation with a threshold value obtained averaging the maximum and minimum gray-level values of the entire image (Fig. 1) and then the ground-area available for cleaning can be estimated.

The trajectory and cleaning coverage originated by the mobile robot is obtained through off-line analysis using three sequential procedures per frame. In the first procedure, the reference ground frame is subtracted from the frame under analysis (Fig. 2-left) obtaining a well defined contour of the mobile robot (Fig. 2-right) that can be located in the image searching the vectors obtained by addition of all the columns and all the rows of the image. This subtraction procedure is especially useful because all initial objects, except the mobile robot, disappear in the resulting image (Fig. 2-right) making this localization step very robust. The second procedure is used to detect the marks attached to the robot. The default mark for flat mobile robots is a round white circle (diameter of 14 cm) with a radial dark line (Fig. 2-left), starting in the center of the robot and pointed to the forward mobile robot motion. The line of this mark can be located by a simple segmentation limited to the diameter of the disc; the threshold value to get the line points is obtained averaging the maximum (white disc value) and minimum (dark line value) gray levels inside the disc. Then, the line is obtained by standard regression using the absolute coordinates of the black points located while the projection of the point closest to the center of the disc gives the center of the mobile robot. The third procedure compares mobile robot position and orientation (x, y, α) between frames (Fig. 3) and computes the polygonal area covered by the displacement of the cleaning tool. This polygonal area is first measured and accumulated to get the dynamic coverage evolution and then stored graphically into a dedicated ground layer for visual inspection and other analysis.

3. Modeling floor-cleaning coverage

A set of experimental measurements were developed in the defined cleaning scenario to model floor-cleaning coverage, experiments were repeated at least 10 times to get average evolutions but only individual results are used and shown in this work because they are very representative. The fist set was developed without additional objects inside the cleaning scenario and with the floor already clean. Some mobile robots include an optical sensor to measure the dirty level of the ground and adequate (reduce) speed during the cleaning so the floor was kept cleaned during measurements to avoid this effect. Additionally, mobile robots with different measurement algorithms or exploratory path-planning were used with the default settings assuming that user interaction with the mobile robot is minimized by daily use. The measurement procedure was performed as described in the previous section. First, a reference

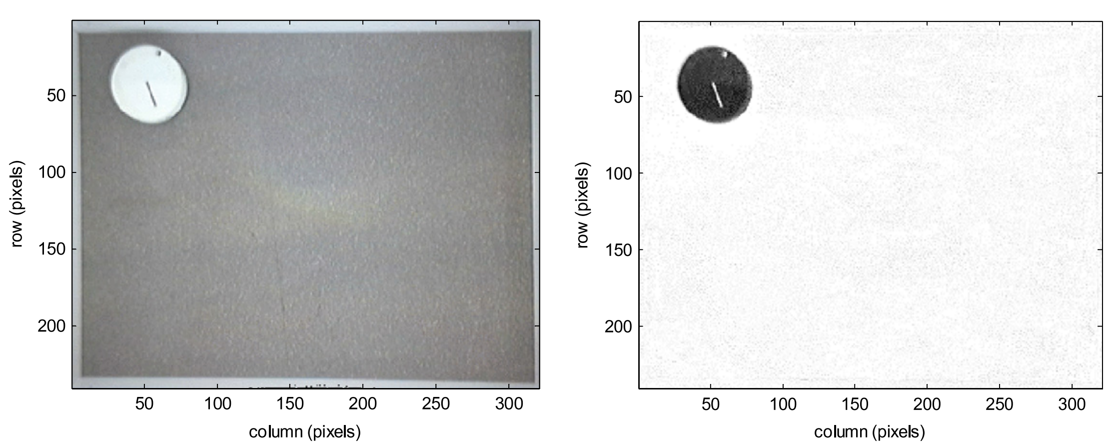


Fig. 2. Typical QVGA image of RoboNet (left) and absolute intensity image after ground subtraction (right: the gray-levels are inverted for easy printing).

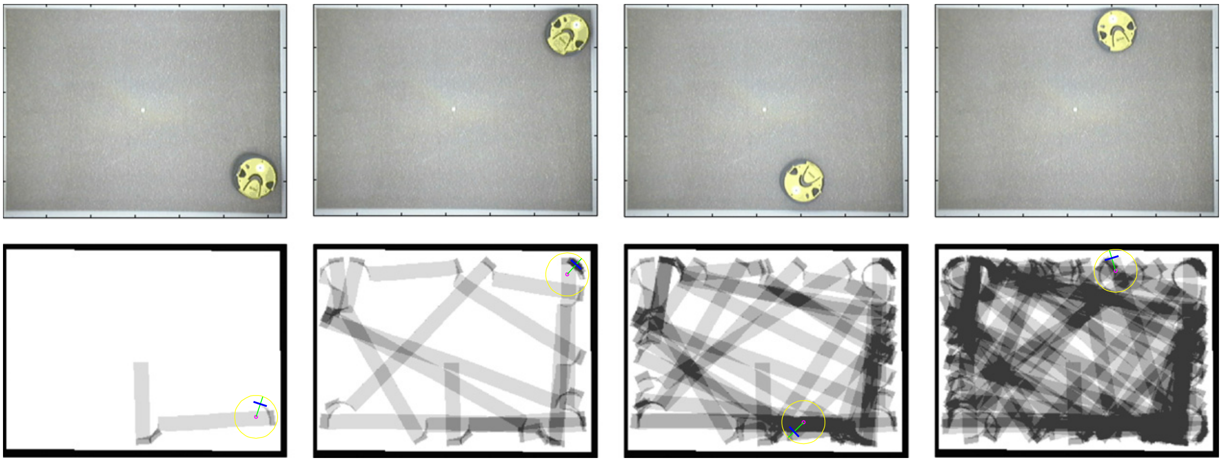


Fig. 4. RC 3000: snapshots of the trajectory at {0.2 2 5 10} minutes (up) and corresponding cleaning path and coverage (down).

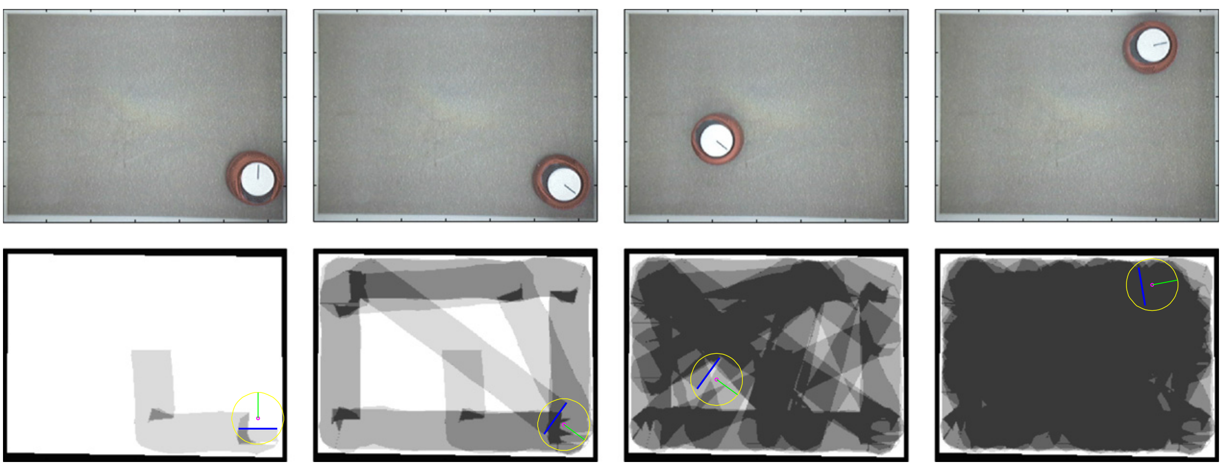


Fig. 5. Trilobite: snapshots of the trajectory at {0.2 2 5 10} minutes (up) and corresponding cleaning path and coverage (down).

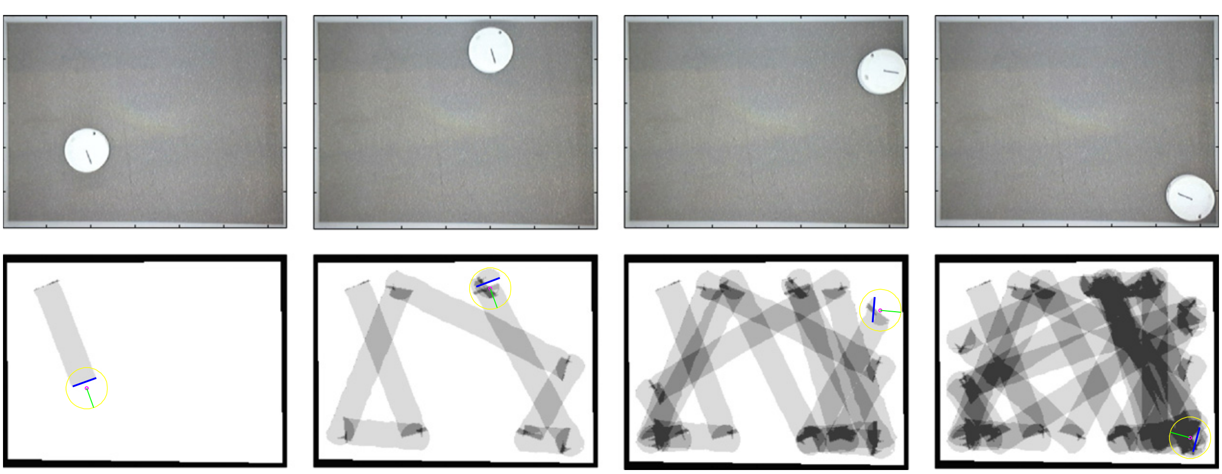


Fig. 6. RoboNet: snapshots of the trajectory at {0.2 2 5 10} minutes (up) and corresponding cleaning path and coverage (down).

background image of the cleaning scenario without the mobile robot is taken. Secondly, the mobile robot with a reference mark was placed in the cleaning scenario. Third, the image recording and then the mobile robot were started.

Fig. 4-up shows a sequence of original frames obtained with the RC 3000 whereas 4-down shows the estimated location and orientation of the mobile robot over the ground layer used to estimate floor-coverage. Fig. 5 are the same for Trilobite, Fig. 6 for RoboNet, and Fig. 7 for Roomba. In Fig. 7 there are two possible floor-coverage evolutions for Roomba with or without the coverage effect of the rotating additional brush included in the front of the mobile robot, an aspect that will be discussed later in this work.

The floor-coverage shown in Figs. 4–7 is coded using five different gray-levels (more dark is equivalent to more passes) to evidence that complete coverage is achieved in all cases although all selected mobile robots cleans several times the same area of the floor, resulting in an inefficient over-cleaning.

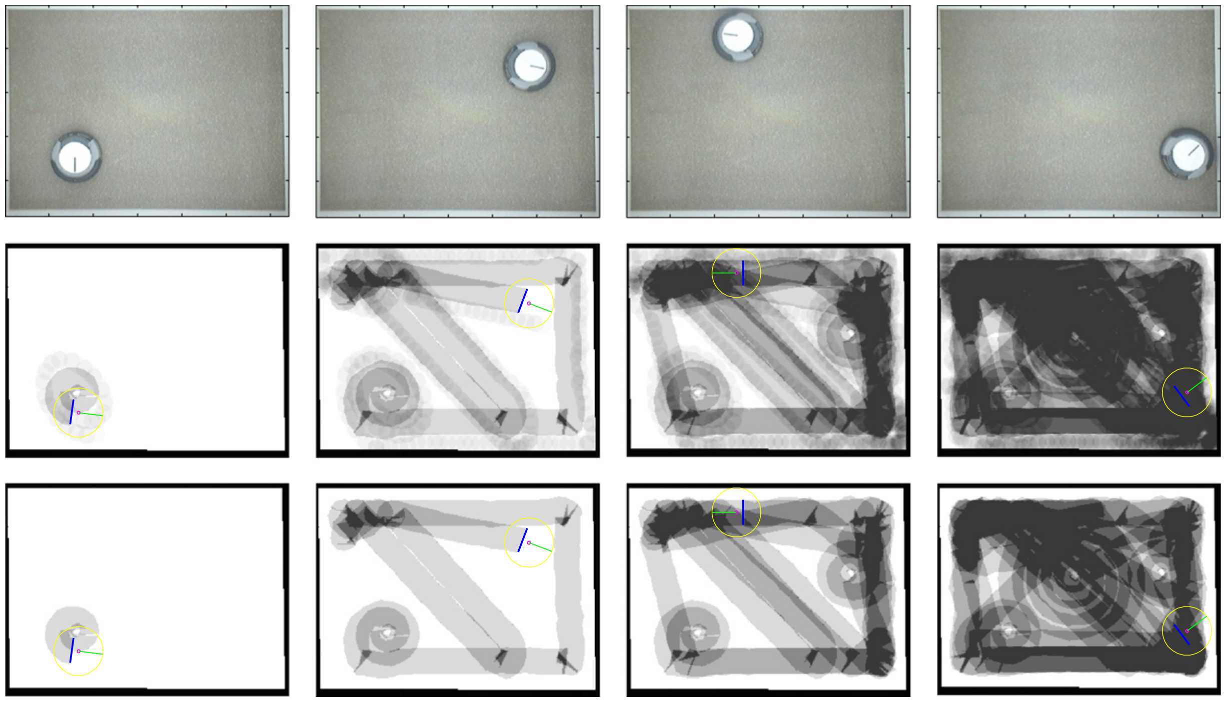


Fig. 7. Roomba: snapshots of the trajectory at {0.2 2 5 10} minutes (up) and corresponding cleaning path and coverage with the additional frontal cleaning brush (middle) and without (down).

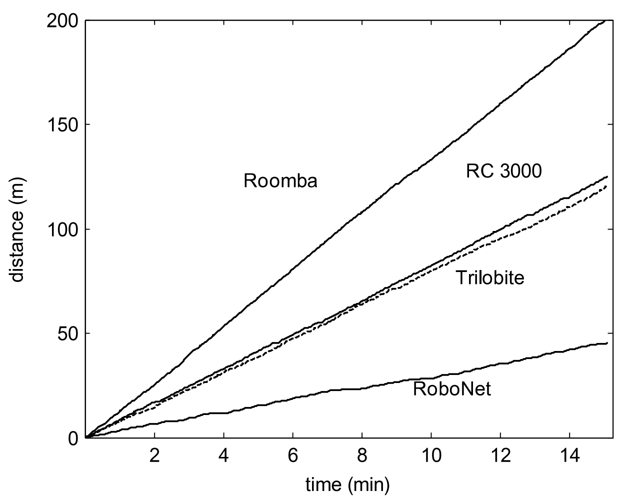


Fig. 8. Evolution of the distance ran by the selected mobile robots.

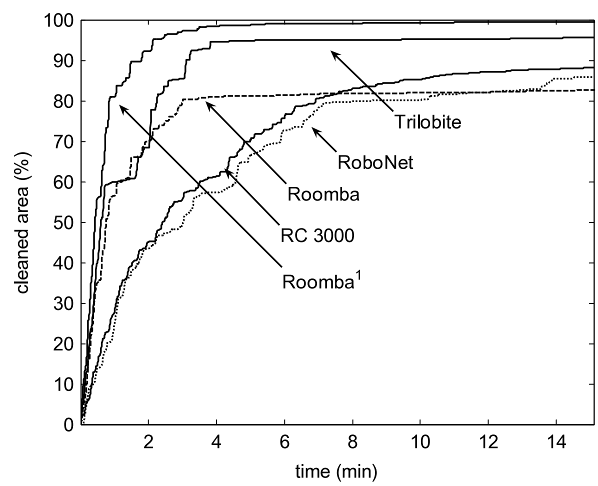


Fig. 9. Dynamic evolution of the total ground-area cleaned with the selected mobile robots.

Fig. 8 shows the evolution of the distance ran by the robots. The evolution is very linear and the average speed was 0.80 km/h for Roomba, 0.49 km/h for RC 3000, 0.47 km/h for Trilobite and 0.17 km/h for RoboNet. The lower speed of RoboNet was intentionally to reduce collision impact because it is a prototype built with very fragile photopolymer. Fig. 9 show the dynamic evolution of the area covered at least one time by the selected mobile robots. Roomba is labeled twice in the figure: "Roomba[1]" corresponds to the cleaning coverage considering the effect of the additional rotating brush included in the front of the mobile robot while "Roomba" corresponds to the coverage without this additional brush. This differentiation was done to evidence the influence of additional cleaning devices in the area covered although, in this particular case, it is not clear if this high speed rotating brush is a real contribution to the cleaning operation because big dust particles can be ejected several meters away from its initial position. Nevertheless, it is not clear if this effect is a real disadvantage because Roomba (and all selected robots) cleans several times the same area of the cleaning scenario increasing the chances to recollect these new ejected dust particles. Evolution shown in Fig. 9 is highly correlated with the speed of the mobile robots that is not a crucial aspect in an automatic and unsupervised floor-cleaning. All cleaning evolutions have an exponential shape except in the case of Trilobite where the perimeter of the room is explored at the beginning although after this initial step the exploration follows a typical exponential evolution. Fig. 10 shows a representation of the floor-cleaning evolution against the distance, first reported in [24]. This representation overcomes the influence of the speed and latency states between mobile robot movements. The initial evolution of the coverage for the selected mobile robots (Fig. 10) is highly correlated with the main brush width. The order defined by the fastest floor-coverage evolution in the first 10 meters are Trilobite (brush width of 260 mm), RoboNet (212 mm), Roomba (170 mm), and RC 3000 (95 mm). As expected, the wider

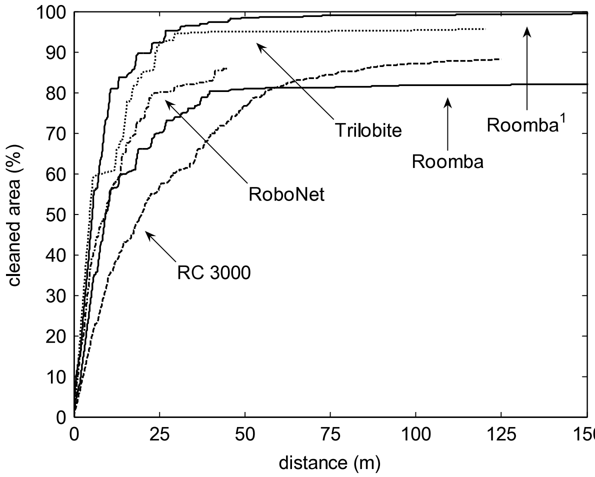


Fig. 10. Dynamic evolution of the total ground-area cleaned with the selected mobile robots.

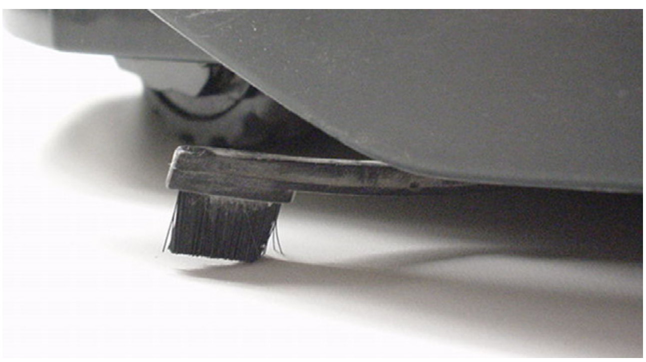


Fig. 11. Additional lateral rotating brush included in Roomba to increase floor-cleaning coverage.

brush results in the fastest performances in the distance domain, but it is also very important to have a smaller size to enter under objects as chairs during the cleaning.

The use of an additional lateral brush in "Roomba1" (Fig. 11) has great impact on the floor-coverage evolution because it gives access to contour areas not available for the other mobile robots. The maximum area covered is highly correlated with how close the robot can go to the walls and the radial distance from the cleaning device to the external structure of the mobile robot that is especially important in the turns after collision with the walls. The order defined by the maximum coverage is Roomba1 (99.5%), Trilobite (95.6%), RoboNet (85.5% in 15 min but 95% with additional time), RC 3000 (88.1%), and Roomba (82.6%).

The relationship between the diameter, cleaning device width, and the relative location of the cleaning device in the mobile robot can be used to define two figures of merit of the cleaning mobile robot design. The first parameter called radial occlusion factor (ROF) is the ratio between the radius covered by the brush (see Fig. 12) and the radius of the mobile robot. The second parameter called brush relative factor (BRF) is the ratio between the cleaning device width and the radius of the mobile robot. Both parameters can be obtained analytically with:

$$ROF = 100 \cdot \frac{rb}{r}$$
$$BRF = 100 \cdot \frac{bw}{2 \cdot r} \qquad (1)$$

where r is the external radius of the mobile robot; rb is the maximum radial distance covered by the cleaning device; and bw is the cleaning device width.

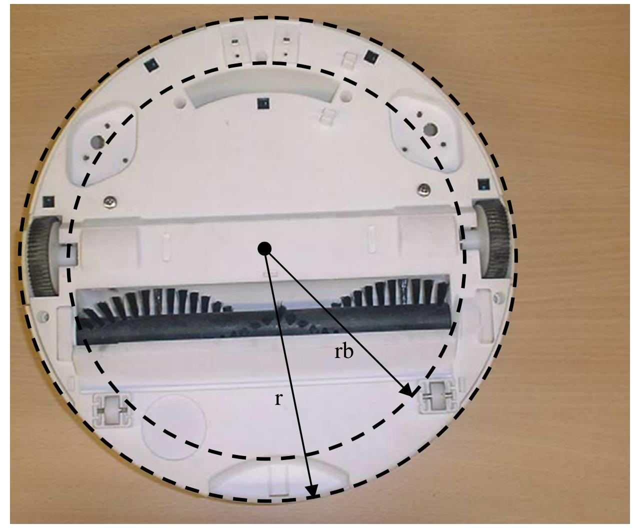


Fig. 12. Representation of the radial distance, *rb*, and the external radius, *r*, for RoboNet.

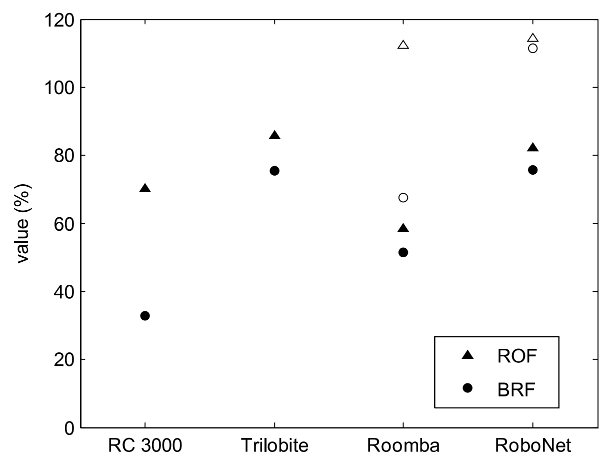


Fig. 13. Figures of merit of the selected cleaning mobile robots. Solid markers where computed considering only the effect of the main cleaning device while empty markers includes the effect of additional rotating brushes.

Fig. 13 shows a graphical representation of the proposed figures of merit for the selected mobile robots. Solid markers are used to depict the obtained values without considering the effect of the additional lateral rotating brush in the cleaning; in this case the maximum ROF is 85.6% for Trilobite while the maximum BRF is 75.7% for RoboNet. Empty markers are used when the lateral additional rotating brushes were considered; in this case ROF is 112% for Roomba1 and 114% for RoboNet (designed to use two lateral rotating brushes) while the maximum BRF is 111% for RoboNet. A ROF higher than 100% means than the robot cleans an area outside its diameter ant then the area covered and cleaned is one pass is maximum whereas an BRF higher than 100% depicts that the mobile robots cleans an area higher than its diameter and then floor-cleaning coverage is higher than robot coverage.

In [24] the shape of floor-cleaning coverage evolution was fitted in the time and distance domain with several exponential models trough least mean squares (LMS). In this work a simplified mono-exponential model with only two parameters, A_{MAX} and Td, defined in the distance domain is proposed:

$$C(d) = A_{MAX} \cdot \left[1 - e^{-d/Td}\right] \qquad (2)$$

where A_{MAX} is the maximum area covered by the mobile robot expressed either in m^2 or %; Td the distance constant of the

Table 2
Image and Area of the different case-configuration of the cleaning scenario.

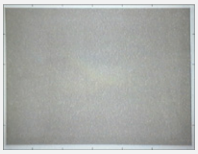
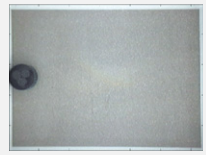
Case A (empty)	Case B (chair)	Case C (bin)	Case D (wall)	Case E (table)
				
2.506 m^2	2.501 m^2	2.452 m^2	2.488 m^2	2.483 m^2

Table 3
Mono-exponential cleaning model obtained by LMS.

	RC 3000			Trilobite			Roomba[1]			RoboNet		
	A_{MAX}		*Td*	A_{MAX}		*Td*	A_{MAX}		*Td*	A_{MAX}		*Td*
Case	(m^2)	(%)	(m)	(m^2)	(%)	(m)	(m^2)	(%)	(m)	(m^2)	(%)	(m)
A	2.21	88.1	24.3	2.40	95.6	8.9	2.48	99.0	14.3	2.15	85.9	10.5
B	2.10	84.1	25.6	2.25	90.2	7.6	2.41	96.3	15.6	2.06	82.2	9.1
C	2.11	85.9	22.2	2.31	94.1	8.5	2.42	98.7	13.6	2.11	84.0	7.6
D	2.02	81.2	20.9	2.27	91.0	6.2	2.44	98.1	15.9	2.01	80.1	7.0
E	2.06	82.9	21.8	2.33	93.9	6.7	2.45	98.7	15.6	2.00	80.0	9.9

[1] Including the coverage originated by the lateral additional rotating brush.

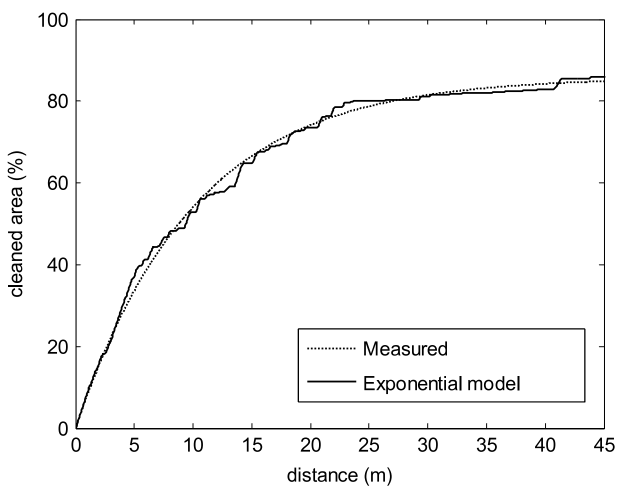


Fig. 14. Measured cleaning evolution and estimated using the exponential model obtained for RoboNet and Case A.

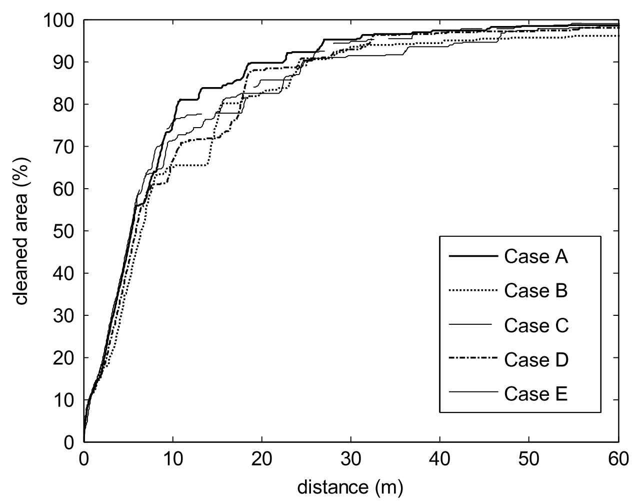


Fig. 15. Measured evolution of the cleaned area for Roomba[1] in the different scenario cases considered.

evolution in meters; d the distance in meters; and $C(d)$ the coverage evolution in the distance domain.

Table 2 shows a new set of different measurement cases defined adding different objects (at a ground level) in the cleaning scenario. The cases considered are: (A) empty scenario, (B) with the legs of one chair, (C) with a waste-paper bin, (D) with a wall in the middle, (E) with the legs of one table. Table 3 resumes the parameters of the exponential model of the floor-cleaning evolution fitted with (1); a smaller distance constant, *Td*, means faster ground floor-coverage. Fig. 14 compares real measurements with the exponential model obtained. Fig. 15 shows the evolution of the floor-cleaning coverage obtained with Roomba for the different cases considered where no significant difference can be observed because the area has a small change between cases because of the small objects. Fig. 16 shows graphically the spectra of all the exponentials obtained; the distance constant, *Td*, of each robot has a variation of $\pm 8\%$ and the maximum amplitude, A_{MAX}, $\pm 3\%$. Note that Trilobite and RoboNet have the smaller distance constant and then they will reach the maximum coverage faster than the other mobile robots. Roomba[1] is the robot that covers the largest amount of the ground area in all cases although its distance constant is not the fastest. This is as a consequence of the exponential shape of the total floor-coverage where the evolution depends on the effect of both, amplitude and distance constant parameters.

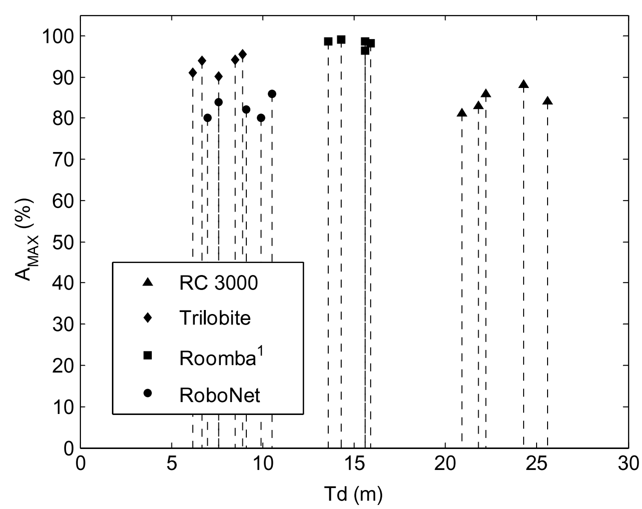


Fig. 16. Spectra of all exponentials shown in Table 3.

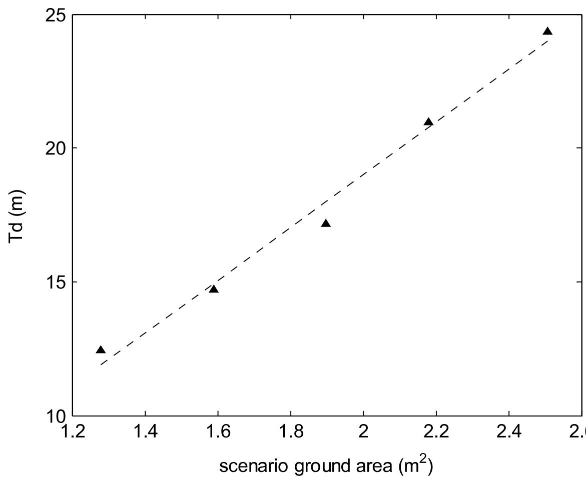


Fig. 17. Dependence between the distance constant of the exponential evolution, *Td*, and the scenario size (dotted line depicts regression data) for the RC 3000.

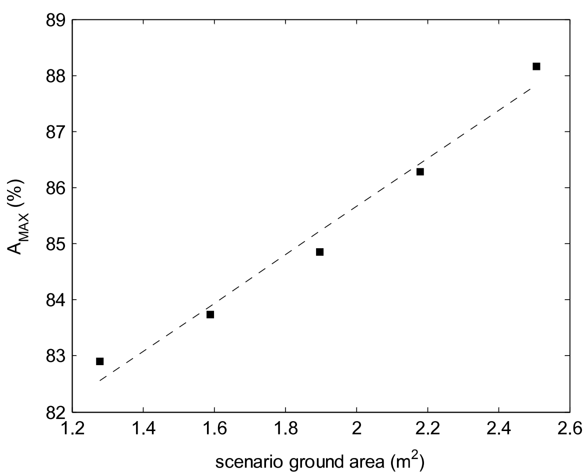


Fig. 18. Dependence between the amplitude of the exponential evolution, A_{MAX}, and the scenario size (dotted line depicts regression data) for the RC 3000.

The last set of experiments was performed to estimate the influence of the room size in the parameters of the mono-exponential model. To this end, the trajectory and coverage evolution obtained with RC 3000 was measured in different rectangular scenario sizes. Figs. 17 and 18 show the evolution of both parameters of the exponential model showing the following linear relationship with the room size:

$$\begin{aligned} Td(a) &= 9.857 \cdot a - 0.710 \\ A_{MAX}(a) &= 4.289 \cdot a + 77.077 \end{aligned} \tag{3}$$

where a is the area of the room in m^2.

This model allows the estimation of the dynamic floor-cleaning coverage of a room whose size is known. The effect of small and big objects is focused in the reduction of the room size and does not affect the value of the distance constant. In a similar way, dynamic objects have no influence in the floor-coverage evolution because the area that is instantaneous blocked by the object will be cleaned in later (or previous) passes. The main drawback of this mono-exponential model is that several experimental measurement procedures are needed to get the model of one mobile robot. Then, if a cleaning mobile robot has a random component in his path, cleaning-coverage evolution can be estimated and then stopped without over-cleaning the floor when the odometry of the mobile robot reaches five times the distance constant:

$$D_{STOP}(a) = 5 \cdot Td(a) \tag{4}$$

where D_{STOP} is the target distance to stop de mobile robot in meters.

Table 4
Model parameters of the mobile robots analyzed.

Robot	ROF (%)	BRF (%)	Average speed (km/h)	Slope of *Td* (m^{-1})
RC3000	70.2	32.7	0.49	9.85
Trilobite	85.6	75.4	0.47	3.54
Roomba[1]	112.1	67.6	0.80	5.61
RoboNet	82.2	75.7	0.17	3.98

For example, applying the model of the RC 3000 in an area of 2.506 m^2 the estimated distance constant, *Td*, is 24.0 m (the measured value was 24.3 m) and the estimated distance stop, D_{STOP}, is 120.0 m, a correct value according the evolution shown in Fig. 10 because for this distance floor-coverage evolution is already saturated. Alternatively, using the average speed of the mobile robot this target distance can be converted in a time limitation to stop the cleaning procedure properly.

Finally, Table 4 resumes the new proposed model parameters of the mobile robot analyzed: the structural factors ROF and BRF are two indicators of the mechanical design of the mobile robot; the average speed is representative of the average displacement of the mobile robot; the slope of the distance constant, *Td*, obtained in the mono-exponential model truly define the dynamic evolution of the coverage achieved by the mobile robot where the smallest slope the fastest cleaning. The maximum amplitude, A_{MAX}, obtained in the mono-exponential model is not included in the table because is room size dependent and is highly correlated with the structural factors ROF and BRF.

4. Conclusions

In this work, the floor-cleaning coverage evolution obtained with some real mobile robots are measured, analyzed and modeled and the main conclusions obtained are:

The external radius of the mobile robot and the width and placement of the cleaning tool are determinant in the cleaning process. Two figures of merit: radial occlusion factor (ROF) and brush relative factor (BRF) have been defined to compare the mechanical design of different cleaning mobile robots. When both values are exactly 100%; mobile robot coverage is equal to floor-cleaning coverage because the effective width of the cleaning device is equal to the diameter of the mobile robot.

An exploratory algorithm based total or in part on a random path planning assures complete coverage of a closed area but resulting in an over-cleaning because some parts of the floor are covered several times by the mobile robot.

The dynamic evolution of the total area cleaned by a mobile robot using a random path-planning control algorithm has an exponential shape even if additional rotating brushes are included in the mobile robot.

The cleaning evolution obtained in a distance domain can be estimated with a single exponential model where the amplitude corresponds to the maximum area cleaned (covered) by the mobile robot and the distance constant to the dynamic evolution of the total area cleaned (covered).

Small objects at the ground level, as the legs of the chairs, have a very small effect on the distance constant of the model of the floor-cleaning coverage evolution when using a random path-planning mobile robot.

The amplitude and distance constant defined in the exponential model are robot dependent and, if the area of the room is known (or can be estimated), the evolution of the total area cleaned by the mobile robot can be estimated before operation and then cleaning procedure can be stopped at five times the distance constant, minimizing the over-cleaning of the floor and the energy requirements of the mobile robot.

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T. Palleja received B.Scd. and M.Sc. degrees in engineering from Universitat de Lleida (UdL), Spain in 2004 and 2006 respectively. He is currently a Ph.D. student at the robotics laboratory of the UdL and his research interests include precision agriculture, mobile robots, human system interaction and educational application of robotics.

M. Tresanchez received B.Sc. and M.Sc. degrees in engineering from Universitat de Lleida (UdL), Spain in 2005 and 2007, respectively. He is currently a Ph.D. student at the robotics laboratory of the UdL and his research interests include mobile robots, precision agriculture and educational application of robotics.

M. Teixido received the B.Scd. and M.Sc. degrees in engineering from Universitat de Lleida (UdL), Spain in 2006 and 2008 respectively. She is currently a Ph.D. student at the robotics laboratory of the UdL and his research interests include human computer interaction, avatar modeling and educational application of robotics.

J. Palacin received the B.Sc. and M.Sc. degrees in electronics from Universitat Politecnica de Catalunya in 1990 and Universitat de Barcelona (UB), Spain in 1997. He received the Ph.D. degree in electronics from UB in 2005. Since 1992 he joined the Department of Computer Science and Industrial Engineering at the Universitat de Lleida (UdL), Spain leading the robotics group. His research area involves compact modeling, data fusion and signal processing applications in robotics.