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NEED FOR VISION SENSING DIMENSION IN MODERN MANUAL-CONTROLLED VACUUM CLEANERS

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Abstract: *Up to this day, many cost-effective vision systems have been successfully used in various domains (such as manufacturing, human machine interaction, robotics, automotive and so on) to provide a new sensing dimension of the working environment. However, there are no such systems implemented for modern manual-controlled vacuum cleaners. The most important usability aspects of integrating such a sensing dimension to modern vacuum cleaners have been explored in this paper, along-with a trivial implementation, to assure the portability and compactness of the cleaning appliances.*

Key words: *vacuum cleaners, computer vision, dirt sensors, vision system.*

1. Introduction

The demand for vacuum cleaners is going to grow at a 5 year compound annual growth rate of 12.5% based on [15], selling up to 5 million vacuum cleaners in 2018. To the best of our knowledge, no vacuum cleaner uses video stream as means of gathering information from the working environment. And in the few cases where cameras are used, they are dedicated mostly for robovacs' navigation, as they are trying to gain understanding on how to move in their environment.

Just a few researchers have proposed the use of a vision system for manual-controlled vacuum cleaners, mainly in tele-operation [16]. Based on the extent of dirt determination through the new vision systems, this process will not only give the machine an initial description of the dirt level, but also will give the operator of that vacuum cleaner a better outlook on the process of cleaning.

According to [3], there are more than a thousand models of vacuum cleaners available on the market at the moment. Most people select vacuum cleaners based on parameters such as suction power, dust capacity, filtration system efficiency and usability. This paper focuses on last parameter, which can be improved by adding the vision dimension. Most modern vacuum cleaners work based on the same principle, but are classified depending on their appearance as shown in Figure 1. Placing a new sensor designed to capture images of dirt/spills on these different types of vacuum cleaners depends on two significant characteristics: the way the vacuum cleaner is moved in order to clean the dirt, and the nearby mechanisms (attachments) of that vacuum cleaner, which can have a closer un-occluded look

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at the dirt/spill. In this section, we expose such essential and relevant components of different types of manual controlled vacuum cleaners, along with the factors that motivate in adding the new vision sensors.

1.1. Parts of the Modern Vacuum Cleaners

There are five different components [4] that form a vacuum cleaner. They have been termed in this paper as follows:

1. The air intake unit (nozzle head): This is the first component which interacts with the environment, as the dirt and dust is sucked in through.
2. The dirt collector: This is the component where the incoming airflow is split into 2: the clean air moves towards the filters and the dirt is stored in the collector.
3. The filtration unit: This component traps airborne particles of different sizes, depending on its class. I.e. the High Efficiency Particle Air (HEPA) filter is normally placed in between the dirt collector and the exhaust system, filtering particles as low as 1 micron in size.
4. The motor unit: The main suction component of any vacuum cleaner that pulls in the air containing dirt and dust inside the herein mentioned components.
5. The outlet: The final component is an accessible system which allows users to empty the dirt.

Based on the attachment of air intake mechanism to the vacuum cleaner, this paper groups the different types of currently available vacuum cleaners (Figure 1) into:

a) Fixed air intake mechanism type or upright styles (Figures 1a-c),

b) Movable air intake mechanism type or handheld air intake style (Figures 1d-f).

As this paper intends to place the vision sensors near the air intake mechanism for any type of vacuum cleaner, grouping is made based on the relative static or dynamic nature of air intake mechanism, in relationship with the other components of the vacuum cleaner.

Fig. 1. *Different types of modern cleaning systems*

1.2. Upright Style Cleaning Systems

The *upright cleaners* (Figure 1a) are commonly found in household (USA and UK), and have an appearance of an entire machine placed on an upright metal rod resting on two big wheels of diameter 3-5 in. Near the air intake which is at the bottom, there usually have rotating brush-rolls that swipe the dirt off the surface and push it towards the air-intake component. At the end of the rod, there is a handle for the user to move the cleaner back and forth, in order to clean that dirt area.

The *carpet cleaners* (Figure 1b) are similar to upright vacuum cleaners but have special power brushes that reach deep into the carpet fibers. Some of these come equipped with a hot water heater, others completely lack the vacuum function.

The *steam mop cleaners* (Figure 1c) are used to steam sanitize hard floors. They appear similar to the upright vacuum cleaners and share some of their characteristics, however, they do not vacuum (except in the case on hybrid steam mops, such as the Bissell Symphony).

Important aspects: In the case of upright units, the air intake moves by pushing the wheels, using the handle, with the operator at a stand-still position. The operator simply starts the motor unit at and moves the machine back and forth to clean the dirt of some rectangular area; the width of this rectangular area is similar to air intake's breadth. Circular trajectories may be achieved either by changing the position of the vacuum cleaner, or by using steering systems such as swivel steering. Although, the operator's view is always un-occluded, moving a heavy upright can cause stress to the operator [9].

Motivation: Most common problem with this type of devices is to know how to move the device back and forth effectively - what is the speed and acceleration at which the device needs to move for sucking in most dirt? If the system can get an instantaneous feedback on machine's movement and cleaning process, it can itself tune the motor unit power to increase or decrease suction automatically or it can allow the operator to manually adjust it, by giving specific indications. Another feature which can potentially increase the usability of the system is the use of 2 video capturing devices which can be placed in the front and in rear of the cleaning system. These cleaning "eyes" may thus asses the efficiency of the cleaner. Last but not least, the operator may i.e. select the right shade of carpet after using a carpet cleaner. By using vision and image processing techniques, the shade of the current dirty carpet can be displayed and modified by the operator to the right look, by simply varying the color model parameters. These parameters will be directly reflected in the adjustment of the suction/cleaning power. Same strategy could be used for steam mops.

1.3. Handheld Style Cleaning Systems

Handheld style cleaning systems include *wet-dry vacuum cleaners* (Figure 1d). Also called shop-vacs, these can store water or exhaust air.

Canister vacuum cleaners (Figure 1e) are commonly found in European households and are intended to have multiple usages, as the air intake is placed on a flexible hose. The dirt collector, which has an appearance of a can, rests on two wheels separated from air intake compartment to extend the reachability of the vacuum cleaner.

Finally, *handheld vacuum cleaners* (Figure 1f) are used for reaching narrow spaces. Despite the fact that they are portable, some of them have powerful motor units and a suction similar to uprights or canisters.

Important aspects: This category of cleaning systems further extends the reach of the air intake mechanism in narrow places. The operators use their hands to have a precise control on the placement of air intake mechanism, which is connected to the other components of the vacuum cleaner via a flexible hollow cord - the hose. Thus, compared to upright style's simple back and forth motion, the air intake mechanism can be operated in complex motions.

Motivation: Usually the hose itself can cause occlusion, and the narrow area may also block user's view. Users might have to remove the flexible air intake mechanism to see the occluded zones. Thus adding a vision sensor near the air intake mechanism and projecting data onto visual device can help solve this problem. This paper tries to enable some of the features made available to the upright style into the handheld style, in-spite of the "not so trivial" motion performed by air intake mechanism controlled by the operators.

2. Hardware/Software Prerequisites and Objectives for Theoretical and Experimental Studies

Considering both styles of vacuum cleaners, this paper explores the possibility of facilitating the following:

- **On-the-fly performance measure:** The qualitative and quantitative factors of dirt sucked in by a vacuum cleaner can be known based on processing the visual inputs. Furthermore, an instantaneous feedback about the system's cleaning operation can be enabled, which can be used to tune the motor unit on-the-fly, thus saving power.
- **Fine visual interaction with the operator:** Locating a visual device the user eases the display of areas with "problems". Not only the visual guidance can be provided to the operator, but also additional input can be received, based on the observations.
- **Introduce programmability:** The system can process additional data and can be controlled variably (using micro-controllers).

There are 4 key problems which need to be addressed by any application involving video processing

- **Raw Data:** Since high resolution details of dirt may not be needed for processing, for this study we could group neighboring pixels of nearly same hue (color) together. Moreover, only a constant subset of the field of view from vision sensor may be required, as it may contain some additional non-relevant parts, such as body of vacuum cleaner itself.
- **Parallelism:** Off-the-shelf parallel architectures can get more expensive than serial architectures. Also, they might contribute in making the processing system bulky. This research makes use of serial algorithms for any subset of an image captured by the vision sensor. This enables the system to utilize any number of micro-controllers to execute algorithms serially, but their collection processes data in a parallel fashion. Hence, this would ensure that the developed system meets real-time requirements for enabling "on-the fly performance measurements".
- **Fixed vision sensors:** This paper uses sensors that are fixated onto the vacuum cleaner. As the vacuum cleaner moves, the sensors move along-with it and capture relative views. The manufacturer which will implement such a system may pre-calibrate sensors' position and orientation parameters, thus requiring no special effort from users, to ensure that cameras accurate and positioned correctly.
- **Statistical algorithms:** Statistical approaches are computationally efficient and give a definitive result. Throughout this paper, we rely on statistical approaches to obtain results, as the problem domain may not need complex object classification.

As one may see, there seem to be multiple benefits in adding one more sensing dimension. To the best of authors' knowledge, this is the first study that addresses the need of vision in manual-controlled vacuum cleaners (although robotic vacuum cleaners implicitly need environment sensing, this is mainly used for navigation). This paper provides a basic formalism to exploit the use of above mentioned advantages and explores the possibility of implementation, based on similar work. Rather than developing a navigation system, the video information is used with other purposes. In section 2 we preset a literature survey. Section 3 introduces a mathematical model, based on which modern vacuum cleaners may possibly use the enhancements/capabilities which come with the vision system.

3. Dirt Detection

Just a few robotic vacuum cleaners come with a vision sensor (most use infrared/ laser/sonar proximity sensors instead).

This may seem physically equivalent to placing a vision system on manual-controlled vacuum cleaner, however, there are few significant differences:

1. *Collision-free motion planning:* The robotic vacuum cleaner moves autonomously through its environment and needs to ensure that it finds collision free regions. Whereas, for manual controlled devices, such feature is not required.

2. *Area coverage and navigation:* The robotic vacuum cleaner needs to ensure that it does not miss any area using various simple techniques like boundary markers or virtual mapping. Again, such technology is not required for manual controlled vacuum cleaners.

3. *Human interaction:* The robotic cleaners needs less interaction with users, and next to none while it performs cleaning operations. Whereas, for manual controlled vacuum cleaners, the users have to constantly handle the device.

4. *Less powerful cleaning capabilities:* The robotic vacuum cleaners are not so efficient in cleaning as the manual controlled ones. Current manual controlled vacuum cleaners rely on their continuous powerful suction to pull up dirt. Such brute force approach, although simple, can increase the power consumption to a great extent, considering that most households contain at least one vacuum cleaner.

The dirt detection has been studied in the field of poultry [10] and in medicine [12]. A floor image could be split into foreground (containing possible dirt elements) and background (containing the floor pattern). A simple idea would be to use the HSV color space, which could classify each color pixel as a foreground or background [1]. There are other various sophisticated approaches for separating foreground from background [11]. For this case, the one of the most suitable and cost-effective methods is the statistical background modelling [6].

3.1. Algorithms and Implementation

Cost-effectively, multiple vision sensors and common positioning sensors used in robotics (such as a 9-axis IMU [7]) can provide the necessary and sufficient means to enable a user-driven vacuum cleaner to take advantage of the vision dimension.

This section covers simultaneously the enhancements introduced and the basic capabilities developed by using those enhancements. The logical functioning of our proposed vision-based user driven vacuum cleaner is shown in Figure 2. This architecture is based on the *Delayed Vision-based Cross-reference Loop* (DVCL)

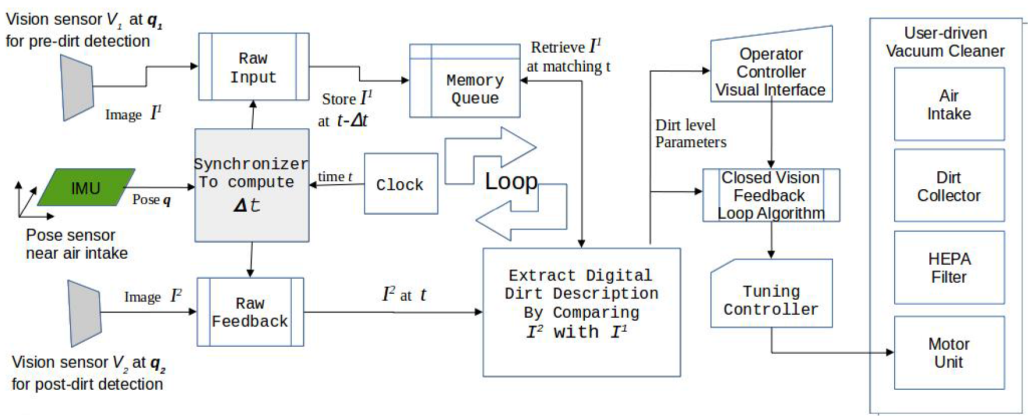

Fig. 2. *Formalism of Delayed Vision-based Cross-reference Loop on any type of manual controlled vacuum cleaner*

formed by a pair of fixated vision sensors V_1 and V_2, and the IMU which returns the pose q of the air intake of the vacuum cleaner. The loop is achieved by the *Synchronizer* process and is termed as *cross-referenced* because it compares two images to give instantaneous result on the level of dirt remaining after the air-intake sucks in the dirt.

3.2. Digitizing Dirt Description

The cross-referencing vision loop determines the extent of dirt being sucked in by the air-intake mechanism of that vacuum cleaner. The visions sensors capture an area A (to be cleaned) successively and their use are described as follows:

- **Vision Sensor V_1:** It behaves like a pre dirt detection sensor, sensing the dirt or spills from the A area. Thus, the image I^1 generated by V_1 contains the workspace information, before the air intake passes through A.
- **Vision Sensor V_2:** It captures the image I^2 of that same area A after the air intake sucks in the dirt; thus V_2 is called as post dirt detection sensor.

Achieving such tight and precise coordination between V_1 and V_2 is only possible with the help of a *Synchronizer* process (as detailed in Section 3.3). The input process performs pre-initializing steps for the image captured by V_1 (such as converting the pixels data from RGB to HSV model), whereas the feedback process performs specialized optimization operations on image generated by V_2, such as highlighting a sub-set of the image where most dirt is sensed by V_1. Algorithm 1 describes the kind of dirt the user is dealing with. Dirt pixels have a different feature f_{dirt} (such as color, appear darker/whiter, similar to white noise in an image) than the area A is resting on. Such distinctive characteristics can support building a classification function CV [5], [13]:

$$\mathrm{CV}\,(\mathrm{I}(x;y),\mathrm{fdirt}) = \begin{cases} true, if\ dirt \\ flase, otherwise \end{cases} \quad (1)$$

Algorithm 1 Extract Digital Dirt Descriptor

1: Input pixels of 2D Images $I^1(x,y)$ and $I^2(x,y)$, $\forall x,y$

2: Input motor unit suction power P_s and dirt feature f_{dirt}

3: $S^1_{dirt}=\{(x,y)\,|\,CV(I^1(x,y), f_{dirt}) = \text{true}\}$

4: $S^2_{dirt}=\{(x,y)\,|\,CV(I^2(x,y), f_{dirt}) = \text{true}\}$

5: **Dirt description #1:** $|S^1_{dirt}|$ gives the amount of contamination of dirt or spill.

6: **Dirt description #2:** $|S^1_{dirt} \cap S^2_{dirt}|$ gives the measure $m(P_s)$ of effective suction by the motor unit.

7: **Dirt description #3:** Measures $m(P_s)$ also determines the adhesiveness of the dirt.

3.3. Cleaning Motion Patterns

One common usage of most vacuum cleaners is to move the air intake mechanism in a particular pattern to suck in dirt; let $\Gamma_{motion} = \{(q, t)\}$ be such a trajectory (based on same principles used in robotics [2]), which is a sequence of distinct poses q (position and orientation) of the air-intake mechanism at a corresponding time t. $\boldsymbol{\Gamma}_{motion}$ will usually have a repetitive pattern where the movement of the air intake starts from pose q_s and ends at pose q_e, moves back from pose q_e to pose q_s, and repeats until most dirt is sucked in by vacuum cleaner. Let the trajectory $\Gamma_s^e(t_r)$ represent motion of the air intake from q_s to pose q_e and $\Gamma_e^s(t_r)$ from pose q_e to q_s, both being a function of time t_r. Thus, a trajectory Γ_{motion} of the air intake mechanism moved by an operator can be described by the following Equation:

$$\Gamma_{motion} \approx \bigcup_{r=1}^{r=d}\left(\Gamma_s^e(t_r) + \Gamma_e^s(t_r)\right), \quad (2)$$

d is number of complete motions required to clean the dirt. d can be estimated using the *Dirt Descriptor* (Algorithm 1); moreover, d can be displayed on a screen to the user, based i.e. on a specialized GUI. The trajectory of the cleaning motion Γ_{motion} can be recorded easily by using the calibrated 9-axis IMU, from which the set of poses $\{q\}$ can be inferred over time t. Computing Γ_{motion} will enable following basic functionalities:

1. Computation of various physical parameters, such as the speed of the vacuum cleaner, the reach of head nozzle and so on.
2. Provides visual interactive guidance on a stress-free cleaning trajectory (as the extent and adhesiveness of the dirt can be determined in Algorithm 1, an optimized trajectory can be provided to the user).

3.4. Incorporating On-The-Fly Cleaning Guidance

"On-the-fly cleaning guidance" describes a system that can offer indications on the cleaning process instantaneously. Knowing such information is a basic necessity for vacuum cleaners to get feedback based on the vision dimension. This feature works based on the DVCL principle (Figure 2), using two vision sensors and knowing (better said, estimating) Γ_{motion}.

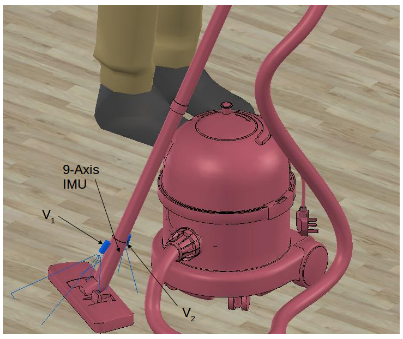

Fig. 3. *Placements of vision sensors V_1 and V_2 near the air intake mechanism with calibrated 9-axis IMU*

Figure 3 shows an example on how to implement V_1 and V_2 as pre/post dirt detection sensors. The vacuum cleaner model is designed with a standard CAD software and imported in a simulation environment provided by Coppelia Robotics [14].

To cross-reference I^1 with I^2 and find out how much dirt has been sucked in by the air intake, the sensors V_1 and V_2 are placed after/below the air intake. As the physical pose of air intake mechanism can be measured using a 9-axis IMU, the locations q_1 (of V_1) and q_2 (of V_2) can be found using the transformation matrix [8]. The transformation matrices $\mathbf{T}_{\alpha}^{V_1}$ and $\mathbf{T}_{\alpha}^{V_2}$ are constant, as both vision sensors are fixed near air intake mechanism a. They could be formulated generally with the following equations:

$$q_1 = \mathbf{T}_{\alpha}^{V_1} q\,, \tag{3}$$

$$q_2 = \mathbf{T}_{\alpha}^{V_2} q\,. \tag{4}$$

Using the 9-axis IMU, q (and implicitly q_1 and q_2) can be obtained. Let the delay in cross-reference checking between images I^1 and I^2 be Δt, i.e. time taken for vision sensor V_2 at q_2 to move to q_1. Such delay is not a constant and will vary upon Γ_{motion}, however, as V_1 and V_2 are fixated very close to air intake mechanism, it is more likely that V_2 will reach q_1 in a very short time. Therefore, computing Δt is the core functionality of the synchronizer process and thus, providing on-the-fly guidance to the vacuum cleaner system using information derived from delayed cross-referenced vision sensors. The Algorithm 2 presents the synchronizer Δt prediction over Γ_{motion}. As shown in Figure 2, the *synchronizer* process interacts with *feedback* process and sends I^2 to the digital dirt descriptor (Algorithm 1), having the coincident image I_1 stored in the *memory* process.

Algorithm 2 Synchronizer

1:Set $S_{\Delta t} \rightarrow \varnothing$
2:**while** clock is running **do**:
3: t_c = current time
4: Input pose q of air intake from 9-axis IMU
5: Compute pose q_1 of V_1 using eqn. 3
6: Compute Δt using short-term prediction for V_2 to be at pose q_1 using following function:

$$\Delta t = Short_{Prediction}\ (v_c,\ q_1) \quad (5)$$

where, V_c is current velocity vector derived from acceleration vector measured by IMU
7: **if** $\ni \Delta t$ **then**
8: Enable Raw Input process to store image I_1 in memory

$$S_{\Delta t} = S_{\Delta t} + \{t_c + \Delta t\}$$

9: **else**
10: **report** air intake mechanism was moved in un-traceable direction
11: **end if**
12: t = minimum element in set $S_{\Delta t}$
13: **if** $t = t_c$ **then**
14: The current pose of V_2 corresponds to some previous pose q_1 of V_1 at time $t - \Delta t$
15: Enable feedback process to send in I^2
16: remove t from set $S_{\Delta t}$
17: **end if**
18: **end while**

3.5. Tuning the Suction Power

A vacuum cleaner can consume a lot of power if a constant suction scheme (running with the same intensity all the time) is applied. As the number of vacuum cleaners increases with the number of homes, it may prove to be a costly affair w.r.t. energy conservation, utility cost, and wear and tear of the machine. Such scheme can be termed as a "brute-force approach" in cleaning the dirt, as it uses an over-estimated limit of the suction power. This paper addresses the problem by using the Closed Vision Feedback Loop process. Algorithm 3 assumes that the vacuum cleaner uses a motor unit with a speed which can be varied proportionally with parameter P_s, which represents the suction power of the vacuum cleaner. A higher P_s means a faster motor speed.

Algorithm 3 Closed Vision Feedback Loop

1: Input current pose q_c of air intake from IMU
2: E = $\{\mathbf{q_c} | q_c \in \{q\}$, where $(q,t) \in \Gamma$
3: **if** E is not $\varnothing$ **then**
4: the operator is still performing Γ
5: $D(t_i) \leftarrow$ Dirt Descriptors from Algorithm 1 at current time t_i
6: **if** $D(t_i) \approx D(t_{i-1})$ **then**
Get feedback from operator as not much change in the level of dirt is detected
7: **end if**
8: Compute Reduction factor over time: the quantity of dirt being reduced along the cleaning trajectory
9: Compute adhesive factor (Dirt Descriptor #3)
10: Compute predicted speed
11: Compute orientation change
12: Set suction power P_s based on the factors above
13: **else**
14: New cleaning motion
15: i = 1
16: Based on Dirt Descriptor #1 determine p, the suction power
17: Reduction factor = 0
18: Compute Adhesive factor P_s
19: **end if**
20: Set the motor power to P_s

4. Conclusions

This paper studies on possible enhancements (capabilities) that could be introduced onto any type of manual controlled modern vacuum cleaners using machine vision techniques. The vision is used to determine dirt level on the area to be cleaned using a vision sensor V_1. It studies one step further in providing a feedback mechanism to know the effectiveness of cleaning operation of that vacuum cleaner by placing the vision sensor V_2 after/below the air intake mechanism.

A formalism using Delayed Vision based Cross-referencing Loop (DVCL) is proposed using two sensors V_1 and V_2 working in tight co-ordination to provide useful capabilities to any type of vacuum cleaner. Such capabilities include digitizing dirt description, detecting cleaning motion patterns of the operator using IMU, on-the-fly performance measure of its cleaning operation to provide selectable guidance to the operator, and tuning the suction power of the motor unit to suck in dirt effectively.

For cross-referencing the images generated by two vision sensors at different times an effective coordination mechanism is proposed using calibrated 9-axis IMU.

The paper further studies the complexity of design issues involved in having the proposed capabilities onto any type of vacuum cleaner. The proposed formalism using DVCL achieves these capabilities and further makes the vacuum cleaner programmable for many other features. One solution framework fits all kinds of vacuum cleaners by just involving two vision sensors and a 9-axis IMU.

Algorithm 3 calculates the instantaneous decision that the controller of the motor needs to make based on the parameters derived from the output of Algorithm 1. As in most modern vacuum cleaners, the motor unit is the only main electrical component that makes the suction power functional, thus the algorithm is dedicated only to tune that motor unit. Algorithms 1, 2 and 3 provide enough basic components to operate the DVCL and make modern vacuum cleaners programmable and intelligent.

Adding vision dimension to modern vacuum cleaners can enhance the operators experience in cleaning dirt/spills, while, simultaneously, proving beneficial w.r.t. energy savings, cost cuttings, and efficient cleaning. Moreover, it could provide safety to the operators in having stress-free visual guidance of moving the vacuum cleaner for cleaning (by means of a visual device).

This paper provides sufficient and necessary means to motivate manufacturers of manual-controlled vacuum cleaners in exploring and employing vision as a significant information channel, while keeping the fabrication costs similar to that of robotic vacuum cleaners.

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References

1. Bouwmans, T.: *Recent Advanced Statistical Background Modeling for Foreground Detection - A Systematic Survey*. In: Recent Patents on Computer Science **4** (2011) No. 3, p. 147-176.
2. Craig, J.J.: *Introduction to Robotics: Mechanics and Control. 3rd Edition*. Pearson Prentice Hall Upper Saddle River, 2005.

3. Judson, S.H.: *Remote-Controlled Vacuum Cleaner*. US 840 Patent 6,457,206, Oct., 2002.
4. Kithany, D.: *Small Home & Personal Care Appliances Report - 2014*. IHS Technology, May, 2014.
5. Latombe, J-C.: *Robot Motion Planning*. Kluwer Academic Publishers Norwell, MA, USA, 1991.
6. Lin, Z., et al.: *Development of the Wireless Ultraminiaturized Inertial Measurement Unit wb-4: Preliminary Performance Evaluation*. In: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, 2011, p. 6927-6930.
7. Lowe, D.G.: *Object Recognition from Local Scale Invariant Features*. In: Computer Vision, 1999. The Proceedings of the seventh IEEE International Conference on **2** (1999), p. 1150-1157.
8. Nam, Y.S., et al.: *View-Time Based Moving Obstacle Avoidance using Stochastic Pre-Diction of Obstacle Motion*. In: IEEE Intl. Conf. on Robotics and Automation, 1996, p. 1081-1086.
9. Parish, P.: *Vacuum Cleaners You Wear: Scientific Studies Shed Surprising Light On Backpacks*. 2014.
10. Pearson, T., et al.: *A Machine Vision System for High Speed Sorting of Small Spots on Grains*. In: Journal of Food Measurement & Characterization **6** (2012) No. 1-4, p. 27-34.
11. Salvadori, C., et al.: *An Optimization of Gaussian Mixture Models for Integer Processing Units*. In: Journal of Real-Time Image Processing (2014), p. 1-17.
12. Sural, S., et al.: *Segmentation and Histogram Generation using the Hsv Color Space for Image Retrieval*. In: Image Processing. 2002. Proceedings. 2002 International Conference on **2**, IEEE, 2002, p. II-589.
13. Ullman, S.G., Humphreys, W.: *High-Level Vision: Object Recognition and Visual Cognition. Vol. 2*. MIT Press Cambridge, MA, 1996.
14. http://www.coppeliarobotics.com/. Accessed: 01-10-2015.
15. http://www.explainthatstuff.com. Accessed: 01-10-2015.
16. http://www.vacuumguide.com. Accessed: 01-10-2015.