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Safe Navigation of a Wall-Climbing Robot by Methods of Risk Prediction and Suitable Counteractive Measures

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***Abstract*— Safe navigation on vertical concrete structures is still a great challenge for mobile climbing robots. The main problem is to find the optimum of applicability and safety since these systems have to fulfill certain tasks without endangering persons or their environment. This paper addresses aspects of safe navigation in the range of wall-climbing robots using negative pressure adhesion in combination with a drive system. In this context aspects of the developed robot control architecture will be presented and common hazards for this type of robots are examined. Based on this a risk prediction function is trained via methods of evolutionary algorithms using internal data generated inside of the behavior-based robot control network. Although there will always be a residual risk of a robot drop-off it is shown that the risk could be lowered tremendously by the developed analysis methods and counteractive measures.**

I. INTRODUCTION

Up to now, inspections or the maintenance of large vertical concrete structures are a great challenge for wall-climbing robots. Although there is a large field of application – e. g. in the regular inspections of buildings like dams, cooling towers or bridge pylons – there are still no commercial robots available. Whereas some climbing robots [1], [2] suite well for these tasks but are not robust enough, others [3], [4], [5] seem to climb safely but provide less applicability. Applicability requires e. g. fast navigation speed, high maneuverability, easy handling by the user and high payload in terms of inspection sensors or tools for maintenance. In contrast to that, safety demands a more defensive system behavior to ensure the adhesion even under worst conditions to avoid injuries of the technical staff or damages of the system.

The main problem related to safe robot navigation is based on the fact that the influence of the environment on the robot cannot be described well. In the area of ground-based vehicles this description – e. g. based on geometric considerations – is focussed on locomotion and originates methods of terrain classifications or adaptions of the navigation depending on an estimated or measured impact [6], [7], [8]. But, so far, it is nearly unexplored in which cases wall-climbing robots fail and in which way these cases can either be avoided, or at least reduced in their impact or probability of occurance.

This paper addresses the problem of safe navigation in the range of wall-climbing robots using negative pressure adhesion in combination with a drive system [9]. Here, a malfunction, an unhandled event, or a wrong evaluation of the situation can lead to a drop-off and therefore to strong damages or to a total loss of the system. Due to the increased system complexity compared to ground vehicles – since not only the locomotion, but also the adhesion components interact with the environment – additional analysis elements and measures are needed. The goal is to reduce the probability of a robot drop-off to a minimum by performing a detailed hazard analysis and applying special control methods.

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Section II introduces the prototypic climbing robot CROMSCI and the state-of-the-art in terms of safety systems of mobile and climbing robots. Since standard closed-loop controllers are not sufficient to avoid a drop-off in certain situations, section III presents the behavior-based control elements of the negative pressure system and examines different hazards affecting the robot and methods to detect and avoid risks. Finally, the experimental results are summed up in section IV and conclusion follows in section V.

II. FUNDAMENTALS

Of course, navigation safety strongly depends on the environmental situation and on the capabilities of the vehicle. Therefore, one needs to know the basic technologies of the used robot to get an idea of the challenge in this area.

A. *Wall-Climbing Robot* CROMSCI

The service robot CROMSCI (figure 1) has been developed to perform inspection tasks on large concrete buildings area-wide and semi-autonomously [10]. To fulfill demands like fast navigation speed and high payload it combines several technologies: a negative pressure adhesion system with redundant chambers, an omnidirectional drive system and adaptive sealings. Key data are a diameter of 80 cm, a height of 40 cm, a weight of about 50 kg including an optional manipulator arm, and a payload of about 10 kg. For communication purposes and because of high energy consumption CROMSCI is supported via an umbilical cord.

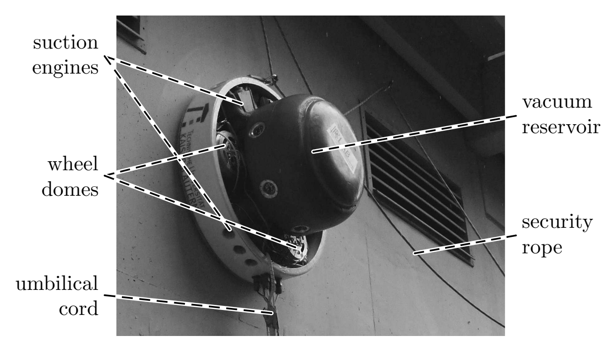

Fig. 1. Climbing robot CROMSCI driving on a concrete wall.

The unique feature of CROMSCI is the negative pressure system consisting of individual adhesion chambers in a shape of spokes with airfilled rubber sealings. This allows a balancing of downforces and torques for the adhesion to vertical or overhead structures. Figure 2 shows a simplyfied model of the system with its seven working chambers (marked with numbers 1 to 7). They are supported by one large reservoir volume (R) on top, which is evacuated by three suction engines. Also an exemplary crack is shown, which influences chambers C_3 and C_7 by an increased leakage.

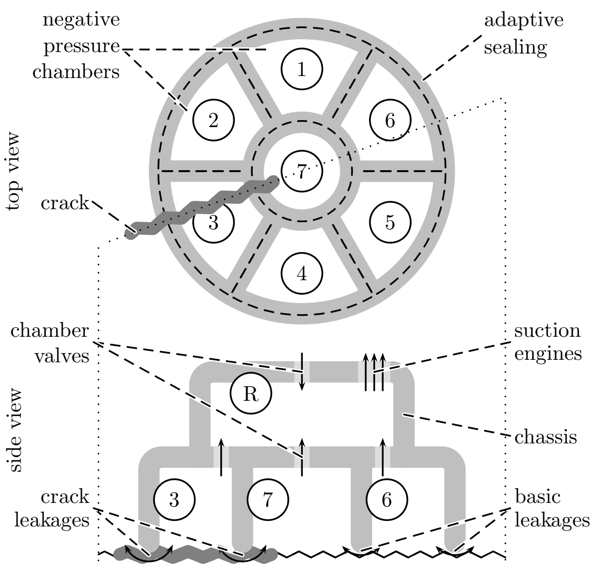

Fig. 2. Structural view of the negative pressure system: Adhesion chambers 1 to 7 and reservoir R with an exemplary crack below chambers 3 and 7.

To allow a closed-loop control of the chamber pressures – generally lying between -100 and -50 mBar compared to ambient pressure – the adhesion chambers and the reservoir are equipped with pressure sensors and connected via valves. In operation, the robot drives at a wall with inflated chamber sealings which glide over the surface and make the system more or less air-proof so that – in general – all vacuum chambers contribute to adhesion. The sealing system consists of an air filled rubber tube at about 1.5 Bar with a coating for improved sliding characteristics. For locomotion CROMSCI is equipped with three steerable standard wheels without suspension allowing high maneuverability in three degrees of freedom and fast continuous motion with a velocity of up to 9.81 m/min. Integrated load cells measure downforces and torques at the wheel contact points.

For collision avoidance CROMSCI is equipped with a light-weighted laser range sensor (Hokuyo URG-04LX). But, its accuracy is too low to detect small surface features or irregularities which can be overcome by the locomotion system, but which have an influence on the adhesion system. Of course, other more precise sensors exist, but, these devices (e. g. light section or stripe projection sensors) are either much too heavy or large, have a long sensing time or a small sensing area. Therefore, internal sensors must be used to analyze the safety state of the robot.

B. *State-of-the-Art in Navigation Safety*

The requirement for safe navigation connects two aspects: Safety and locomotion. For industrial applications but also for mobile service-robots certain guidelines and requirements exist e. g. in terms of international standards for hazard identification and risk reduction. But, especially in the case of climbing machines the robot itself and not the environment is most endangered. In general, four criteria have been defined which are important for safe navigation of mobile robots [11]: Detection, localization, response and throughput. But these guidelines need a detailed analysis of the system and knowledge about its interaction with the environment. The same counts for the analysis of internal components [12] via classic analysis methods like *fault tree analysis* or the interaction between robot and environment depending on precise or very abstract descriptions [13], [14].

Since – in the present case – navigation safety is strongly linked to the adhesion system, common approaches related to navigation safety are not sufficient since they only consider the ability of the locomotion system to overcome certain surfaces and of the detection abilities to survey the robot's surrounding. So far, navigation safety of climbing robots is handled only in terms of closed-loop controllers [1], [15] or sufficient reserves of the adhesion system [16]. Since these common measures are not sufficient to ensure a certain safety of mobile wall-climbing robots like CROMSCI, new approaches of robot control and situation rating are needed. Nevertheless, a final safety measure to avoid a drop-off of the robot is a security rope, as it is also applied here.

III. RISK ANALYSIS AND PREDICTION

In general, climbing robots have to face a couple of hazards during operation. Similar to ground-based systems they are in danger of a collision or have to face permanent problems like wheel-slip or abrasion. Also internal malfunctions of hard- and software may lead to damages, but their probability of occurance is comparably low in the present case. But, since adhesion is an additional dimension here, further hazards may occur which are strongly related to surface characteristics and defects at the building (figure 3).

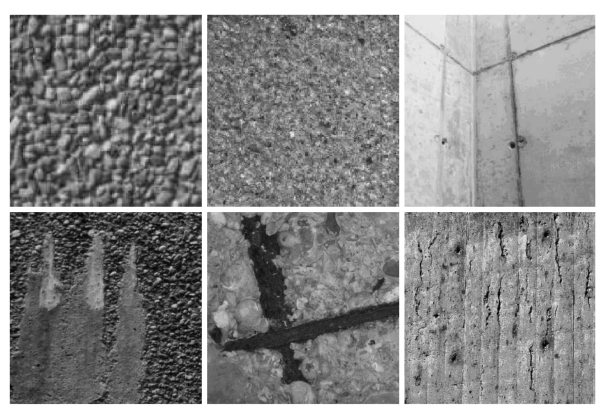

Fig. 3. Different surfaces, contruction characteristics and defects: washed-out and roughened concrete, formwork joint, rock pockets, exposed core iron and spalling (from top left to bottom right).

Sources of these hazards can be the general surface structure like exposed aggregate concrete, sheathing gaps or edges, but also spalling or rock pockets, which are influenced by the weather and general stress. So far, it is not known in which way the negative pressure system is affected if the robot reaches these surfaces and whether it will fail or keep adhered. This is also caused by missing statistical data, which would be needed to create a model describing the interaction between robot and surface sufficiently.

A. Robot Adhesion Control

Because of missing knowledge and statistical data as well as suitable sensors for a foresighted detection, other solutions are needed to analyze the safety state of the robot. The idea is to take internal information from the control network of CROMSCI into account. This network consists of components of the behavior-based control architecture iB2C[1] [17] and reaches from closed-loop control up to high deliberative functions. In general an iB2C *behavior* is an algorithmic element with an arbitrary transfer function F (figure 4) generating control data $\vec{u}$ (e. g. valve opening) based on the input vector $\vec{e}$ (e. g. pressure values) and meta data. This interface is the same for all behaviors and uses the following four meta values to signal the current state and to influence other behaviors: *Stimulation* $s \in [0,1]$ activates the behavior which enables its task execution; *inhibition* $\vec{\iota} \in [0,1]^v$ reduces or annihilates the effect of a stimulation; *activity* $\vec{a} \in [0,1]^w$ shows the real amount of action the behavior is performing and *target rating* $r \in [0,1]$ shows how satisfied the behavior is in the current situation. Additionally, general elements for arbitration or interaction exist like *fusion* behaviors to combine outputs of behaviors trying to control the same resource or behavioral *groups* to create logical units.

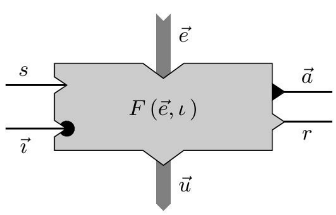

Fig. 4. Elementary behavior module in the iB2C architecture.

The adhesion control system itself consists of a network of 47 behavior elements [18]. As input, the network receives e. g. desired force values and it delivers valve positions for chamber pressure control. The *force control* behaviors try to adjust this amount of total downforce and its point of action. They make use of the lower part of the network as a kind of actuator, which consists e. g. of the *chamber control* behaviors executing the closed-loop pressure control. Here, for instance, the activity value corresponds to the valve opening whereas the target rating depends on the difference between desired and current chamber pressure. For safety reasons it is also possible to cut off single chambers from the remaining adhesion system if the leakage of this chamber is too large due to surface defects. Corresponding *deactivation* behaviors analyze the single chamber state, shut them down and reactivate them if possible.

[1] http://rrlib.cs.uni-kl.de/mca2-kl/libraries/ib2c/

B. Risk Prediction Method

This adhesion control network works in general, but is not able to prevent the robot from a drop-off in certain situations. The presented approach of using internal information for risk estimation is possible because of the redundant multiple chamber system: Since robot adhesion is created by a couple of chambers some of them may fail for a short period of time without endangering the system. In practice the front chambers in driving direction are exposed to hazardous features first which allows a judgement of the upcoming terrain. Since pressure sensor values itself are not sufficient for risk prediction, virtual sensor values in form of *activity* and *target rating* values of the adhesion behaviors are evaluated. Especially the different target ratings provide information about the state of the adhesion system because they represent individual satisfaction values of controllers like the difference between desired and current value.

The goal is to determine a risk value based on these meta values and an *evaluation function* which is *one* or above if the robot will drop off (if no evasive action is performed). Additionally, this value must stay below one if the robot adhesion is not endangered to avoid false positives. Finally, the risk value should indicate a potential drop off early enough (1-2 s) to allow evasion actions like driving back to a safe position so that the adhesion system can recover. In the current approach a weighted sum $E(\vec{a},\vec{r}) : [0,1]^{2n} \mapsto \mathbb{R}$ is used as evaluation function which applies the meta data of the n behaviors as shown in equation 1.

$$E(\vec{a},\vec{r}) = \sum_{i=0}^{n-1} (w_{a,i} \cdot a_i + w_{r,i} \cdot r_i + ...) \tag{1}$$

At this juncture *activity* a_i and *target rating* values r_i of behavior i are used in combination with corresponding weights $w_{a,i}$ and $w_{r,i}$. In addition it is also possible to take filtered or preprocessed meta values like average, median or variance with according weights into account.

C. Optimization via Evolutionary Methods

The challenge is now to determine the weights of $E(\vec{a},\vec{r})$. Since they cannot be set by hand, an optimization function via an evolutionary algorithm and training data has been developed [19]. Based on training sets and a rating function the weights are changed randomly but goal-leading until they fit the given sets. Each training set contains the behavioral meta values of every time step and a so-called *adhesion score* $S_A \in [0,1]$ indicating the current state of the adhesion system (equation 2). This score (and therefore the chance of a drop-off) raises if the adhesion force F_z becomes smaller or if the position of its point of action (x_F, y_F) departs from the center. Here, d^{max}, F_z^{max} and F_z^{min} denote thresholds for distance from center and downforce values respectively.

$$S_A = \max\left(0, \min\left(1, \max\left(\frac{\sqrt{x_F^2 + y_F^2}}{d^{max}}, \frac{F_z^{max} - F_z}{F_z^{max} - F_z^{min}}\right)\right)\right) \quad (2)$$

The goal is to predict a raise of this score S_A early enough to start counteractive measures. Therefore, a population P of possible solutions is optimized to fit certain criteria, as published in [19]. Each individual c is one set of weights $\vec{w}$ (one weight for each used meta value). One evolution step, starting with the current population $P(s)$ at step s, can be summed up as follows:

1) Determine fitness $F(c)$ of all individuals $c \in P(s)$ of the current population based on quality of prediction.
2) Cancel the optimization process if an individual meets the desired criteria.
3) Randomly select individuals c with probability $p(c)$ for the intermediate population $P'(s)$ (survivors).
4) Adapt the weights of the survivors $c \in P'(s)$ via *mutation* with certain probabilities.
5) Set updated $P'(s)$ as new generation $P(s+1)$ and continue evolution with the children.

The most difficult aspect is the calculation of the fitness value which depends on criteria like the avoidance of false-alarms and desired notifications of a robot drop-off in the training phase. Here, an individual is *fit* if evaluation E from equation 1 in combination with the individual's weights is a good prediction of the adhesion score S_A from equation 2.

To describe this relationship in an algorithmic way, a rating function R_E compares the evaluation result $E(t)$ of an individual with the corresponding adhesion score $S_A(t)$ of that training set over time. Three different aspects are taken into account: At first, $E(t)$ should *stay below* $S_A(t)$, otherwise the rating value R_E is diminished by a penalty. Second, *unwanted values* must be avoided which produce false alarms. Therefore, a penalty is added based on the differences of $E(t)$ and S_A in cases of too early notifications or false alarms. In the same way a penalty for *missing desired values* can be applied, if the adhesion score S_A of this training set signals a drop-off without that $E(t)$ predicted this (reached a value above 1) a certain time span earlier.

In practice, the evaluation system has to be trained once and can be applied to similar situations and setups. The results of the complete system regarding the detection and false alarm rates allow a good prediction of upcoming hazards, as already presented in [19]. In terms of safety, this analysis is essential to enable the robot to identify hazardous situations soon enough to initiate counteractive measures.

D. Case-based Prediction of Risks

But, experimental results of the training process have shown that it might be impossible to find sets of weights that fit strongly differing situations. Driving upwards a wall and driving downwards e. g. are completely different for the adhesion system since in the first case the top chambers – which have to adjust a higher negative pressure to balance out robot tilt – first reach a surface defect. In the second case the lower chambers reach the disturbance which do not contribute much to the overall downforce. Therefore, the complete risk prediction system considers three different situations which have to be trained independently: *Driving down* the wall, *driving up* and *driving horizontal*. Since robot movement is a combination of horizontal and vertical motions the prediction needs to be sensitive for two situations in parallel if the robot e. g. moves up and sidewards. Similar cases like driving left and driving right are handled by mirroring the weights which are applied to behavior values having a horizontal twin due to a symmetrical robot setup.

E. Counteractive Measures for Risk Avoidance

Beside the mentioned adhesion control structure there also exists a behavior network for robot motion control. Whereas some basic safety measures like a traction control system or a shear force controller have been integrated on embedded electronics [10] this network is used for high level control. Figure 5 illustrates the components (middle) which are responsible for the six basic robot motions: *turn left*, *turn right*, *drive forward*, *drive right*, *drive backward* and *drive left* (left out here). Two of them are combined via a fusion behavior (dark gray boxes below) to determine the final amount of turning, straight or sideward driving. The fusion behaviors above are needed to allow a triggering of these motions from different higher behaviors like a GUI.

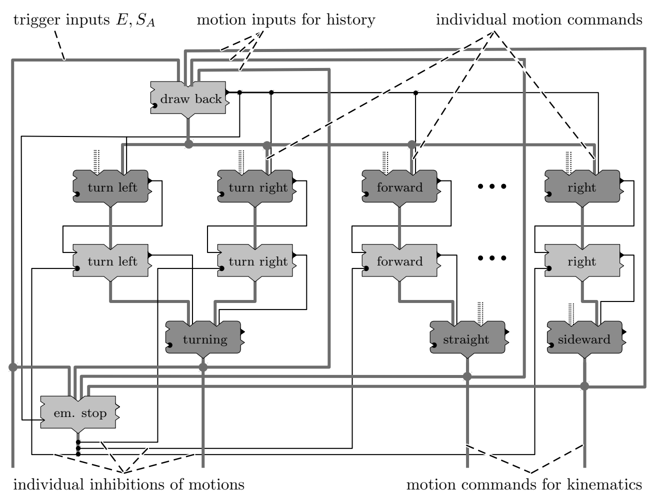

Fig. 5. Behavior-based network for basic robot motions and embedded counteractive behaviors to avoid a robot drop-off.

Here, two important counteractive measures have been developed to avoid a drop-off of the robot: *Emergency stop* and *draw back*. Depending on the current situation the *emergency stop* behavior can inhibit motion commands pointing in the same direction as the last ones. By this mechanism the robot stops driving into the current direction but the user is still able to rescue the system by driving it backwards manually. A more sophisticated measure is the *draw back* behavior on top which actively triggers robot motions to replay the last motions in the opposite way. This behavior is activated by the risk prediction value E.

IV. EXPERIMENTAL RESULTS

The complete system of adhesion and motion behaviors, detection, analysis and counteractions has been tested inside of a simulated environment first to validate the general functionalities of the presented methods [20]. Afterwards, some real experiments were executed with the real prototype.

A. Experimental Setup and Preparation

To prove the approach under field conditions training data from the real machine is needed to optimize the evaluation function by finding suitable weights. For data collection and subsequent experiments a wooden indoor test wall has been used. The advantages of this setup are the easy adaption of the wall (e. g. creation of holes and grooves) and the independence from weather. In the test runs CROMSCI has been driven sidewards several times until the end of the wall where the robot is not able to stay adhered and drops off.

In total four training sets have been created: Three with a drop-off of the robot (secured by a rope) and one without, in which the end of the wall was not reached. The last one is important to avoid false alarms whereas the others are needed to get to know critical situations. Figure 6 depicts the adhesion score values S_A of all training sets as dashed gray graphs. In solid black the optimized evaluation values E for risk prediction based on the trained weights are shown which should reach a value above 1 one to two seconds before the adhesion score S_A is at 1 as reaction time.

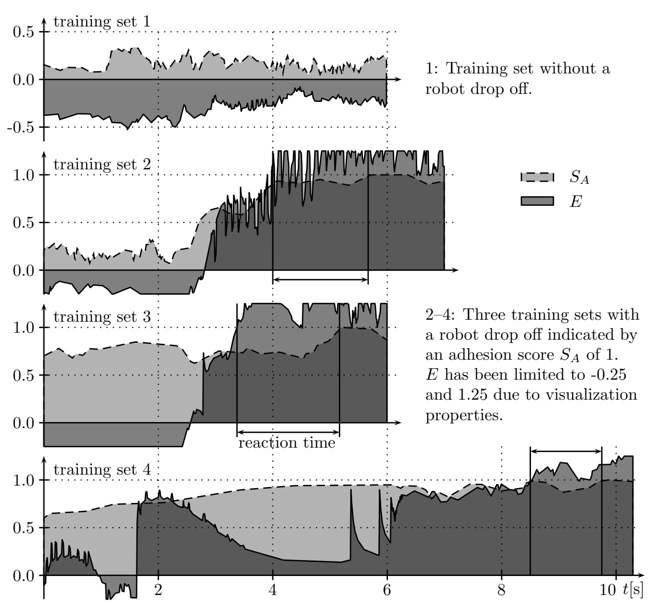

Fig. 6. Resulting evaluation values E (solid black) for the used four training sets based on the learned weights and adhesion scores S_A (dashed).

B. Experiments on a Concrete Wall

After some preliminary and successful tests on the wooden test wall, the prediction of risks and the corresponding safety measures are executed under real conditions on a concrete wall outside of a building. Again, the same setup – driving beyond the wall's edge – has been chosen because it leads to a repeatable robot behavior (drop-off). Due to the high dynamic of the system it can be stated that the robot is in a similar but not the same situation as before. This shows the robustness against some dissimilarities of the evaluation since the training sets of the wooden wall are used here. Nevertheless, it was possible to record only a small set of training data and to perform a small number of validation runs due to hardware limitations. Figure 7 shows videos stills[2] of a test run. It can be seen that the system behaves in the desired way and moves backward away from the hazard.

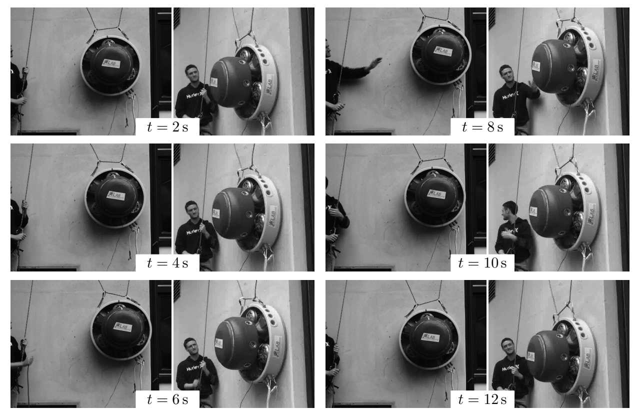

Fig. 7. Video stills of prediction and avoidance experiments on a concrete wall (frontal and side view).

Figure 8 depicts the development of the downforce F_z, the point of downforce $\vec{P}_F$ and the rating values S_A and E. Although the estimated risk E is a bit irregular, it signals an upcoming drop-off at $t \approx 7.2\,$s which triggers the automatic counteractive measures in terms of the draw back behavior. It can be expected, that the risk estimation is even better if training examples of that particular situation are added to the optimization process to update the weights.

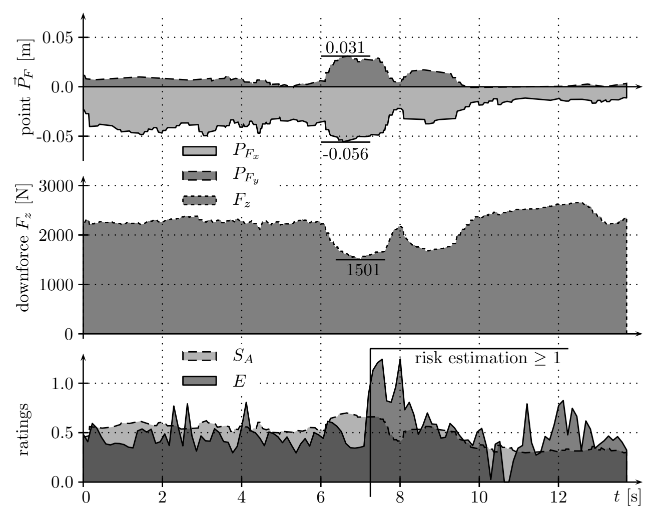

Fig. 8. Position and value of point of downforce (top, middle), adhesion score S_A and estimated risk E (bottom) at a concrete wall.

[2]The complete video can be found at `http://agrosy.cs.uni-kl.de/en/galerie/cromsci-medien/`

The interaction of the motion control network from section III are depicted in figure 9. Here, the GUI behavior is active (first row) all the time to allow a manual steering of the robot. The robot is driven by hand half-speed forward and right as it can be seen by the activities a_F and a_R with values of about 0.5 (compare video stills in figure 7). Up to this point the *draw back* behavior (DB) is allowed to be active due to an activation value $\iota_{DB} = 1$ but its activity is zero. Due to the rising risk prediction value at $t \approx 7.2\,\mathrm{s}$ – as shown before – this behavior is triggered and becomes active ($a_{DB} = 1$). This causes two things: At first the two active motion behaviors controlled by the user (GUI) are inhibited which causes an activation ι and therefore also an activity a of zero ($a_i \leq \iota_i$ counts for all behaviors i). Second, the last motion commands are replayed by the *draw back* behavior the other way around. This is done by stimulating the opposed behaviors *backward* and *left*, as it can be seen by the raising values of a_B and a_L with the same activity values as used before. At second 11 the robot reached a safe state and stopped for a recovering of the adhesion system.

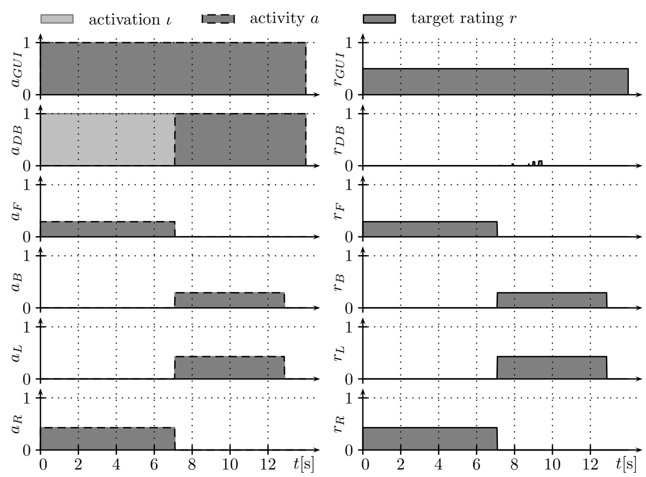

Fig. 9. Meta values of behaviors GUI (user input), *draw back* (DB) and of the four motions *drive forward* (F), *drive backward* (B), *drive left* (L) and *drive right* (R).

V. CONCLUSION

This paper presented a method of risk prediction and corresponding safety measures for safe navigation of a wall-climbing robot. The prediction is based on meta data of a behavior-based control network and calculates a risk value which points out if the robot is going to fail within the next two seconds or not. A situational prediction has been developed to handle the three main motion directions up, down and sidewards. Corresponding safety measures, which let the robot escape from hazardous situations, have been developed and tested. All in all, the experimental results are very satisfying, although further tests are needed to validate the functionality of this approach in the field. In fact, more situations and different surface structures have to be tested to get to know the limitations of the system and whether it is possible to find weights, which are suitable to a broad kind of surfaces, or not.

Next steps are the development of a new and more reliable climbing robot and to transfer the presented approach including controllers and risk measures to the new adhesion system using eleven chambers. This would also allow the generation of more test examples and statistical data.

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