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Intelligent Traction Control for Wheeled Space Vehicles

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Abstract: - This paper presents the SC-MER, Safety Control for Mars Exploration Rover, an innovative traction control scheme for wheeled mobile vehicles. The system is thought to be used on space mission rovers and is based on fuzzy logic and competitive neural networks to achieve optimal navigation on rough terrain with variable morphology. The main goal of this research is to minimize the power consumption needed during the navigation and improve the overall stability and safety of the rover itself.

1 Introduction

In the last years we assist to a growing international interest in deep exploration of wide open regions of the Martian surface. An exhaustive comprehension of planet's terrain, its geology and exploration characteristics is of great importance to the whole scientific community. Nonetheless the last results in planetary rovers have supplied with the technologic means needed for semi-autonomous robot navigation through relatively safe terrains [1,2]. For a conventional wheeled rover, this usually means mobility over continuous natural surfaces having rock densities of 5-to-10%, modest inclines (<30%), and an hard support base to guarantee the right operation conditions in terms of wheels pressure and traction. With the term semi-autonomous we refer to the operations executed by the rover and given remotely by an human expert (with extensive time delay, in planetary cases) and a series of actuations guided by onboard sensors, to be used in typical problems as obstacle-avoidance and path-planning [3,4,5]. The open challenges in scientific research and optimization of rover's operations tend to improve their autonomy and operational safety , given the tight bind in terms of power consumption and safety-keeping of scientific data [6]. The main aim is to supply a robust platform with fault-tolerance and graceful degradation characteristics [7,8].
This paper presents the SC-MER, Safety Control for Mars Exploration Rover, an innovative control system for wheeled space vehicles.
This control system differs from the others because it has been created for terrains with high dangerous access extending the autonomous navigation capability to achieve optimal performances on terrain with variable geometry and changing geological characteristics. The need to supply new generation rovers with these peculiarities is motivated by scientific studies which prove that water presence on Martian surface Is to be found on narrow insets and obstacle-rich zones, making the exploration with a traditional approach unfeasible.
The reference vehicle used in the definition of the control system introduced in this paper is the Opportunity rover, recently employed by NASA in Mars Exploration Rover (MER) project (see Fig 1). This rover is supplied with fully independent wheels and a high definition camera mounted on front.
The target will be to guarantee the rover the safe exploration of his surrounding environment, supplying accurate information on safety conditions. The main components of the control system are realized using fuzzy logic and artificial neural networks. Their use is motivated by the desire to deal with uncertainty and emulate human judgement based on heuristic reasoning on rough terrain driving experience.
In the next sections the details of the proposed architecture will be pointed out: in section II motivations

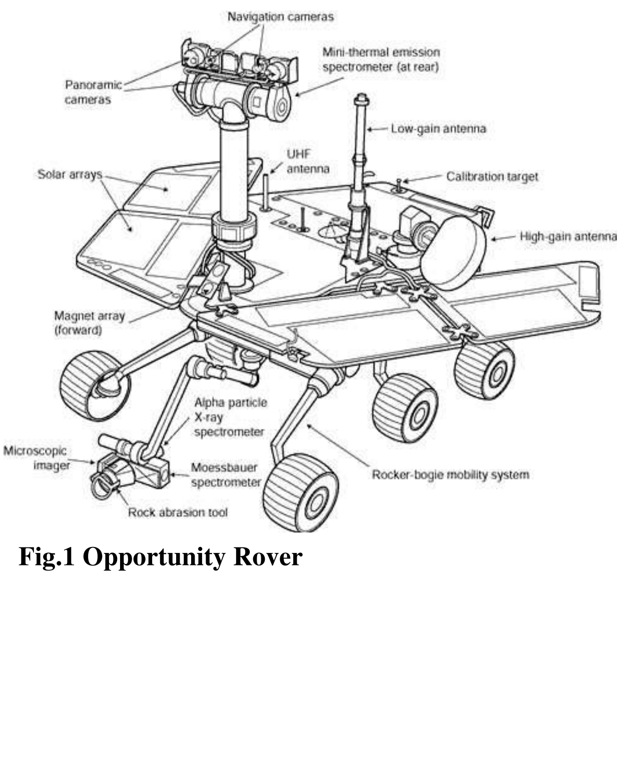

Fig.1 Opportunity Rover

for the new control system will be explained, in section III there will be an exhaustive description of the neural network used for traction control, in section IV we will focus on fuzzy logic for balance control and finally in section V on the experimental results obtained during simulations.

2 Terrain Adaptive Traction Control

In the absence of some measure of control, wheeled vehicles are prone to loss of traction under certain terrain conditions. While on dry paved roads, traction performance is maximal for most wheeled vehicles due to the high coefficient of adhesion between the road and the tread, on off-road terrain, with variable morphologic conditions, rover wheels are subjected to slippage, because of the minor adhesion between wheel itself and the surface. Typical situations pointing out this kind of phenomenon include the presence of sand, gravel, mud and wet terrain. The loss of traction coming from these situations may lead to an excessive vehicle's instability (sudden changes of traction situation may cause sharp acceleration/deceleration which, together with movement inertia, may lower the general control hold), with serious consequences for position estimation, power consumption and onboard equipment and devices safety.
The attitude of the vehicle chassis with respect to an inertial reference frame can be measured in terms of his projection onto a three dimensional space (pitch, roll and yaw) as shown in Fig. 2. Having the longitudinal axis direction equal to vehicle's movement vector, the angles to be monitored in order to control traction repartition are pitch and roll. Recording these values in relation to the mentioned inertial reference frame (which is stable by definition) a metric on terrain travelling across can be associated and used on traction control [9].
To solve the problems depicted above, a new control system is presented, namely the Terrain Adaptive Traction Control (TATC), shown in Fig. 3, and built upon two modules: the Safe Attitude Management (SAM) and the Traction Management (TM).

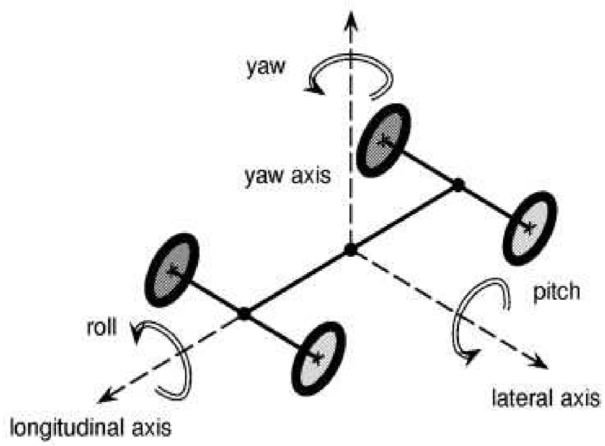

Fig. 2 Degrees of freedom during navigation

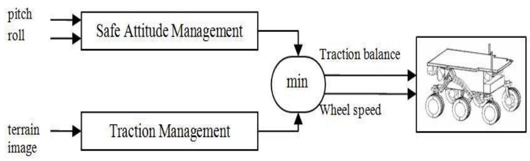

Fig. 3 Terrain Adaptive Traction Control

The SAM's task is to provide information about current rover attitude. While for indoor mobile robots, mobility and navigation problems can often be addressed in two dimensions (x and y) since the typical operating environments consist of flat and smooth floors, In sharp contrast, mobility and navigation problems for outdoor rough terrain vehicles are characterized by significantly higher levels of difficulty. This is due to the fact that complex motions in the third dimension (z) occur quite frequently as the vehicle traverses undulated terrain, encountering multi-directional impulsive and resistive forces throughout.
For monitoring chassis attitude, the vehicle is outfitted with a two-axis inclinometer/tilt sensor, which measures pitch and roll angles relative to a Cartesian reference frame that is aligned with the rover chassis coordinate frame when the vehicle rests on a level surface. The goal of the TM is to optimize traction balance throughout each single wheel, using a visual inspection of the terrain. Classic approaches to this problem make use of wheel mounted tachometer encoders to obtain the traction situation on line. Unfortunately nonlinearities and time-varying uncertainties due to wheel-ground interactions further complicate the problem, making it difficult to use in critical missions as planetary navigation. In this work a soft-computing approach is used instead, which is not based on this kind of sensor but identifies terrain characteristics upon a real-time visual analysis of the terrain in front of the rover using statistical information extracted from it and finally used to establish the optimal selection of actuation for the navigation.

3 Traction Management

The approach used for the classification of terrain typology is based on a visual analysis of his texture, emulating human judgement and reasoning on general appearance of texture itself. The architecture of TM is presented in Fig. 4.
The camera mounted on the front side of the vehicle frames and captures a snapshot of the terrain which lies in his field of view FOV. The monochromatic image is normalized using ordinary low-pass filtering (to remove the noise) and then under-sampled to produce a

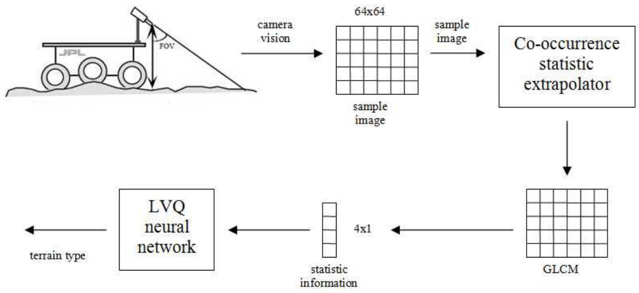

Fig. 4 Traction Management

64x64 pixel, 8 bit-per-pixel, version. From this image, statistic
information summarizing texture characteristics are drawn out using the co-occurrence matrix method. The result is a four-element column vector which embodies all the information needed to further classify the terrain kind.

The classification is obtained using an LVQ (Learning Vector Quantization) Artificial Neural Network, which allows to define membership classes used to the comparison with the input images.

At the final stage of this chain, the type of terrain is recognized and, using some look-up tables known a priori, optimal traction and navigation parameters are identified.

3.1 Co-occurrence statistic extrapolator

Given a translation integer t, a co-occurrence matrix CM of a region is defined for every couple of grey-level (a,b) by

$$CM(a,b)=\mathrm{card}\{(s,s+t)\in R^2 \mid A[s]=a, A[s+t]=b\}$$

CM(a,b) is the number of sites couples (s,s+ t), separated by translation vector *t* with *a* the grey-level of *s* and *b* the grey-level of *s+t.*

Gray level co-occurrence matrix (GLCM) is one of the most known texture analysis methods and estimates image properties related to second-order statistics using the co-occurrence matrix definition depicted above [10,11]. Unlike first-order statistic methods, which are based on the occurrences of each grey-level of the original image, second-order ones measure the simultaneous co-occurrence of the same grey-level on two different pixels separated by a fixed value and along a direction vector.

In order to estimate the similarity between different grey-level co-occurrence matrices, 14 statistic features extracted have been proposed from them. To reduce the computational complexity, only some of these features were selected. The description of 4 most relevant features that are widely used in literature is given below in Tab.1 (P is a nxn matrix, n being the number of grey-level)[12,13].

Energy is a measure of textural uniformity of an image; it reaches its highest value when grey level distribution has either a constant or a periodic form.

A homogenous image contains very few dominant grey image will have fewer entries of larger magnitude resulting in large value for energy feature. In contrast, if the P matrix contains a large number of small entries, the energy feature will have smaller value.

Entropy measures the disorder of an image and it achieves its largest value when all elements in P matrix are equal. When the image is not texturally uniform many GLCM elements have very small values, which implies that entropy is very large. Therefore, entropy is inversely proportional to GLCM energy. Contrast is a difference moment of the P and it measures the amount of local variations in an image. Inverse difference moment measures image homogeneity. This parameter achieves its largest value when most of the occurrences in GLCM are concentrated near the main diagonal. Inverse difference moment is inversely proportional to GLCM contrast. The statistical characterization of sample images is effective, having very low vector distance values for images with similar texture.

3.2 Learning Vector Quantization

In this context a LVQ, Learning Vector Quantization, method has been used for recognizing the type of terrain. Fig.5 .

This network has first a competitive layer and second, a linear layer. The competitive layer learns to classify input vectors like the networks of previous section. The linear layer transform the competitive layer into target classification defined by the user. We refer to the classes learned by the competitive layer as subclasses and the classes of the linear layer as target classes. Both the competitive and linear layers have one neuron per class. LVQ networks have been successfully employed in user defined visual pattern classification area [14].To recognize the type of terrain the networkhas been trained on a sample images set representing the common surface texture known on Mars.Given a 64x64 pixel images, statistical information have been extracted using GLCM method. Ten subclasses have been defined for the competitive layer (the number has been chosen via experimental results), which are later projected onto the three main target classes of the linear layer. These classes rep-

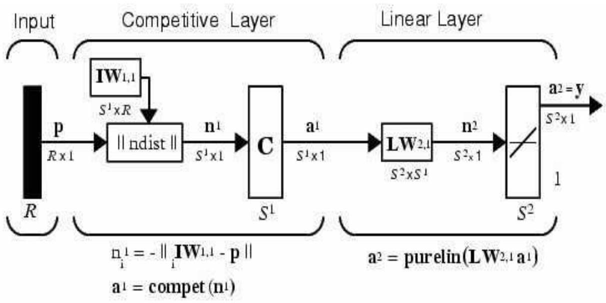

Fig. 5 LVQ architeture

resent the type of terrain recognized by the system. The final output is one of the following column vector.

4 Safe Attitude Management

With a traditional approach the problem of stability in terms of rover's pitch and roll angles is solved by using safety thresholds; when these ones are reached the control signal that serve as reference for wheel motion is suddenly reset [15]. The great restriction in this strategy lies in the intrinsic non-linearity associated with the threshold, which does not take account of near-instability situations. Moreover the typical solution which consists in the attempt to stop the vehicle, ignores kinetic forces of inertia, which could lead to instability and danger for vehicle safety.

On the contrary in this study the monitoring of vehicle attitude is based on a fuzzy system. The admissible pitch and roll angles range, as given by inclinometer sensors, has been partitioned into fuzzy sets to express the inner uncertainty of measurements. The pitch angle is represented by five fuzzy sets with linguistic labels {NEGHIGH, NEGLOW, ZERO, POSLOW, POSHIGH}, while the roll angle is represented by the labels {NEG, ZERO, POS}. Both values are used for two different purposes: to establish the suggested rover

speed and to set the appropriate traction balance on wheels.

Three outputs are defined, the first two to be used for traction balance (front/rear and left/right) and the last one for the suggested navigation speed.

For the traction control a simple linear mapping between roll and traction_LR and between pitch and traction_FR membership functions are provided. The resulting rules are:

IF pitch is NEGHIGH THEN tractionFR is REARWHEELDRIVE AND optimalspeed is SLOW

IF pitch is NEGLOW THEN tractionFR is REARWHEELDRIVE

IF pitch is ZERO THEN tractionFR is ALLWHEELDRIVE

IF pitch is POSLOW THEN tractionFR is FRONTWHEELDRIVE

IF pitch is POSHIGH THEN tractionFR is FRONTWHEELDRIVE AND optimalspeed is SLOW

IF roll is NEG THEN tractionLR is BALANCELEFT

IF roll is ZERO THEN tractionLR is EQUALBALANCE_LEFTRIGHT

IF roll is POS THEN tractionLR is BALANCERIGHT

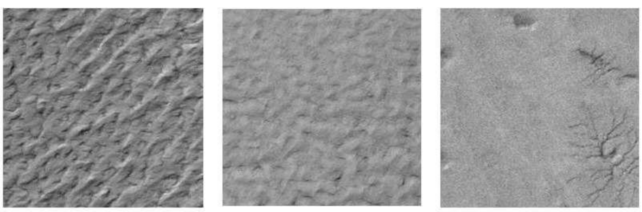

Fig. 6 Different terrain types

Defuzzification method is obtained using the bisector method.

5 Implementation and experimental results

The control system is implemented using MATLAB running on a Pc equipped with an Amd Athlon 2700+ cpu, 512 Mb Ram and Windows Xp Professional operating system.

The input for LVQ network is represented by the GLCM obtained from sampled images. The neural network is realized using the Neural Networks Toolbox 4.0.1; it accepts a 4-elements column vector as input, containing statistical characterizations of image obtained from GLCM matrix. For the computation of statistical features the co-occurrence distance chosen is equal to 1 (that is, the chromatic co-occurrence between a pixel and his 4-neighbourhood).

The competitive layer recognizes 10 subclasses, which are later transformed into the 3 target classes by the linear layer. These classes represent the three types of terrain known to the system and recognized by the neural network. A training set of 150 sample images has been used, having 50 images for each terrain type (Fig. 6).

With regards to the neural network layers number, the choose has been determined by repeated simulation attempts with the aim to lower the matching error. It emerged that the network ability to generalize over dif-

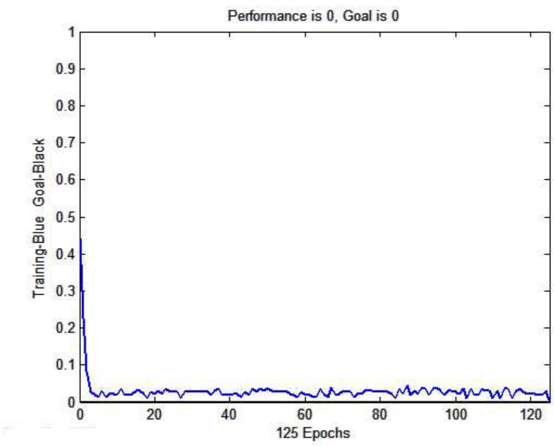

Fig. 7 Matching error in competitive layer neurons

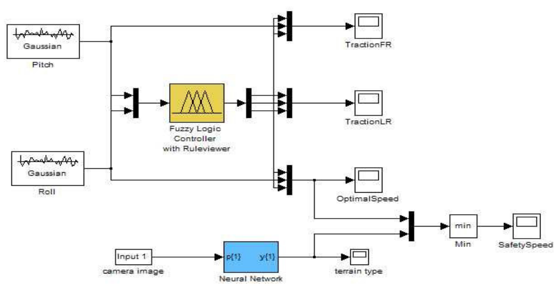

Fig. 8 Control systems simulation

ferent inputs is directly influenced by the number of training epochs and competitive layer neurons, as briefly depicted in Fig. 7 which shows the plot of matching error on increasing training epochs (the error itself refers to the matching using inputs from training set).

It emerges clearly from experimental results that two different configurations have proved to obtain full texture recognition. For cost reason, the second choice was keep because, despite the learning phase was slower, the final implementation was realized using only ~0 competitive layer neurons instead of 50. From a more accurate inspection it results that, the lower is the learning rate coefficient, the better are the final results, and that is proven by the evidence that, using a learning rate coefficient equal to 1 (the highest possible value) the network behaves badly (over-learning).

The fuzzy rules used in traction control arc implemented using the FIS editor supplied by the Fuzzy Toolbox 2.1.

The control system, after having defined fuzzy rules and trained the LVq network, is simulated using the Simulink environment supplied by MATLAB 6.5 using the block scheme shown in fig. 8.

6 Conclusions

A new advanced way to deal with traction control for rover navigation over rough and dangerous terrain (Terrain Adaptive Traction Control) has been exposed. While with a traditional approach the locomotion over slippery surfaces serious wheel slippage phenomenon occur, leading to a waste of power, position estimation errors and overall instability, the new soft computing one is based on fuzzy logic (Traction Management) to automatically balance the wheels traction and suggest the optimal speed, and an LVO neural network (Traction Management) that, using a visual inspection of terrain images, establishes the optimal speed in terms of rover safety. The experimental results have been obtained using MATLAB simulations under Simulink.

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