Dynamic contact sensing for articulated tracked vehicles

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I. Introduction

Articulated tracked vehicles (ATVs) are widely used on applications where terrain conditions are difficult and unpredictable, or the environment may be hazardous for humans [3]. Depending on their mechanical design, these robotic platforms can either increase or decrease the contact area of tracks with the ground, providing better traction on harsh terrains and, on the other hand, energy saving on horizontal nearly-flat surfaces. Such flexibility greatly depends on the ability of the controller to accurately adapt the active sub-tracks, namely *flippers*, to the terrain shape. In principle, the robot can relay on its perceptive capabilities to locally model the terrain and define a trajectory over this approximation. However, the complexity of the whole robot motion, e.g., due to the undefined contact points between the flippers and the terrain, greatly reduces the application of this method in practice. One effective solutions is to allow a compliance interaction between the flipper and the terrain. This approach completely avoids any control and modeling efforts over smooth surfaces, but also reduces the effective traction of the flippers. Still, on terrain discontinuities, care must be taken to avoid trapping the robot or part of it (e.g., on emergency stairs in urban scenarios).

Clearly, any control strategy depends on the contact interaction between the flippers and the ground, and thus, the detection or sensing of the contact event may provide valuable information to the control design. By considering any flipper unit as part of a tree-shaped open kinematic chain rigidly attached to a mobile base, we can unveil the contact event by resorting to state-of-the-art dynamic collision detection strategies for robot manipulators, extended to ATV platforms. In other words, we assume that the contact event can be identified as an unexpected collision of the flipper with the unknown terrain. In particular, we are interested into exploit the generalized momenta Fault Detection and Isolation (FDI) [4], where the collision detection is based on unexpected transient perturbations of the failure signal dynamics. The failure signal, or residual, is obtained through a non-linear observer of the arm generalized momenta.

Formally, the extension of the FDI approach to our case requires an accurate knowledge of the mobile platform dynamics, and thus, an accurate model of the terrain. In particular, as stated in [1][2], FDI cannot be achieved on one particular input channel in the presence of non structured disturbances acting on the same channel. That is, any unexpected motion of the mobile platform introduces disturbances resembling those introduced by a collision of the flipper. However, by assuming that the platform displacements and terrain fluctuation introduce disturbances that are limited by to some low-band frequency range, we might expect that the residual signal may present some disturbance patterns that can be identified and possible discriminated by those generated by unexpected hight-frequency collisions of the flippers with the ground. Our idea is to model the dynamic of the residual as a linear combination of two disturbance sources, that can be identified by its evolution patterns. To this end, we propose a statistical learning approach to estimate (i) the disturbance patterns and (ii) the mixing model to allow both the decomposition and classification of any residual signal.

II. Problem statement

Each flipper unit can be modeled as a single joint manipulator attached to a common base link. For an inertial base link, the whole system dynamics is described by:

$$\mathbf{M}(\mathbf{q}) + \mathbf{c}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau}_T = \boldsymbol{\tau} - \boldsymbol{\tau}_D \qquad (1)$$

where $\mathbf{q}$ and $\dot{\mathbf{q}}$ are the measured joints position and velocities of the flippers, $\mathbf{M}(\mathbf{q})$ is the positive definite symmetric inertia matrix, $\mathbf{c}(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}}$ is the Coriolis and centrifugal vector, $\mathbf{g}(\mathbf{q})$ is the gravity vector and $\boldsymbol{\tau}_T$ is the total torque acting on the system. This torque is given by the difference between the commanded torque $\boldsymbol{\tau}$ and the unknown disturbance torques $\boldsymbol{\tau}_D$. For a moving base link undergoing small accelerations we can rewrite the disturbance vector as:

$$\boldsymbol{\tau}_D = \boldsymbol{\tau}_M + \boldsymbol{\tau}_U \qquad (2)$$

Here $\boldsymbol{\tau}_M$ and $\boldsymbol{\tau}_U$ represent the disturbance due to the non modeled dynamics of the moving base link and the unexpected disturbances, respectively. Based on the generalized momenta FDI framework, the residual signal $\mathbf{r}$ is governed by:

$$\mathbf{r} = \mathbf{K}\left[\int(\boldsymbol{\tau} - \boldsymbol{\alpha}(\mathbf{q},\dot{\mathbf{q}}) - \mathbf{r})\mathrm{d}t - \mathbf{p}\right] \qquad (3)$$

where $\boldsymbol{\alpha}(\mathbf{q},\dot{\mathbf{q}})$ depends on the system dynamics, $\mathbf{p}$ represents the generalized momenta $\mathbf{p}=\mathbf{M}(\mathbf{q})\dot{\mathbf{q}}$ and $\mathbf{K}$ is a positive definite diagonal matrix. It can be shown that $\mathbf{r}$ correspond to a exponentially stable linear filter driven by the unknown disturbance $\boldsymbol{\tau}_D$ [1], that is:

$$\dot{\mathbf{r}} = -\mathbf{K}\mathbf{r} + \mathbf{K}\boldsymbol{\tau}_D = -\mathbf{K}\mathbf{r} + \mathbf{K}(\boldsymbol{\tau}_M + \boldsymbol{\tau}_U) \tag{4}$$

Since the dynamics of the mobile base link depends on the unknown shape of the terrain, we cannot provide an explicit model of the disturbance $\boldsymbol{\tau}_M$. However, we can assume that the disturbance patterns of the dynamics (and thus of the residual $\mathbf{r}$) generated by the motion of the base link are directly related to both the pattern fluctuations of the terrain and the bounded control inputs generating the motion. Therefore, assuming that the terrain is defined by a compact sufficiently smooth surface and that the control velocity inputs also bounded in amplitude and frequency, we can express the disturbance $\boldsymbol{\tau}_M$ as a linear combination of a certain number of n_M basis functions $\boldsymbol{\phi}_i$. Analogously, we can assume that the collision of the flippers with the terrain is defined by a set of n_U basis functions $\boldsymbol{\varphi}_j$, such that:

$$\boldsymbol{\tau}_M = \sum_{i=1}^{n_M} a_i \boldsymbol{\phi}_i, \qquad \boldsymbol{\tau}_U = \sum_{j=1}^{n_U} b_j \boldsymbol{\varphi}_j \tag{5}$$

Let $\Delta\boldsymbol{\phi} \triangleq \mathrm{span}\{\boldsymbol{\phi}_1, \ldots, \boldsymbol{\phi}_{n_M}\}$ be the span generated by the basis functions $\boldsymbol{\phi}_i$, and $\Delta\boldsymbol{\varphi}$ the space generated by the basis functions $\boldsymbol{\varphi}_j$. Assuming that any pattern $\boldsymbol{\tau}_M$ cannot be expressed as a linear combination of the basis $\boldsymbol{\varphi}_j$ and, analogously, any pattern $\boldsymbol{\tau}_U$ does not lie entirely on the span $\Delta\boldsymbol{\phi} \cap \Delta\boldsymbol{\varphi}$, the disturbed residual evolution can be expressed as:

$$\dot{\mathbf{r}} = -\mathbf{K}\mathbf{r} + \mathbf{K} \sum_{k=1}^{n_D} c_k \boldsymbol{\gamma}_k \tag{6}$$

where the $n_D \leq (n_M + n_U)$ basis functions $\boldsymbol{\gamma}_k$ are a subset of the basis $\boldsymbol{\phi}_i$ and $\boldsymbol{\varphi}_j$ such that $\Delta\boldsymbol{\gamma} = \Delta\boldsymbol{\phi} \cup \Delta\boldsymbol{\varphi}$, with $\Delta\boldsymbol{\gamma} \triangleq \mathrm{span}\{\boldsymbol{\gamma}_1, \ldots, \boldsymbol{\gamma}_{n_D}\}$, i.e. the span generated by the $\boldsymbol{\gamma}_k$ basis functions. Given a residual dynamic and assuming that the basis $\boldsymbol{\gamma}_k$ are known, the computation of the coefficients c_k can lead to the identification (classification) of the disturbance source. Therefore, our contact sensing problem can be addressed trough the identification of the unknown set of basis functions $\boldsymbol{\gamma}_k$.

We assume that the set of basis $\boldsymbol{\gamma}_k$ includes all $\boldsymbol{\phi}_i$ and $\boldsymbol{\varphi}_j$ basis functions and that n_M and n_U are unknown. Under this set of assumptions, we can re-write the disturbed residual evolution in eq. (6) as follows:

$$\dot{\mathbf{r}} + \mathbf{K}\mathbf{r} = \mathbf{K} \left[\sum_{i=1}^{n_M} a_i \boldsymbol{\phi}_i + \sum_{j=1}^{n_U} b_j \boldsymbol{\varphi}_j \right] \tag{7}$$

which highlights that the problem of estimating the whole set of basis $\boldsymbol{\phi}_i$ and $\boldsymbol{\varphi}_j$ can be divided into two sub-problems: (i) estimating the set $\boldsymbol{\phi}_i$ from experiments with disturbances induced by the non modeled dynamics generated by the motion of the base link and, (ii) estimating the set $\boldsymbol{\varphi}_j$ from experiments simulating the unexpected collisions of the flippers.

Yet, to decompose any residual signal and discriminate the underlying disturbance sources, we have to determine, upon estimating the set of basis $\boldsymbol{\phi}_i$ and $\boldsymbol{\varphi}_j$, the two mutually exclusive subsets of basis characterizing the corresponding type of source, that is, the identification of the subset of basis not generating the span $\Delta\boldsymbol{\phi} \cap \Delta\boldsymbol{\varphi}$.

III. Proposed Approach

Let us assume that each term $\boldsymbol{\tau}_M$ and $\boldsymbol{\tau}_U$ can be modeled as a mixture of Gaussian Processes (GP) with unknown number of components. Under this assumptions, the aforementioned sub-problems can be addressed by learning the parameters of two different Dirichlet Process-Gaussian Process (DP-GP) mixture models [6, 7].

Next, the identification of the subset of basis generating the span $\Delta\boldsymbol{\phi} \cap \Delta\boldsymbol{\varphi}$ can be obtained as follows. We validate each learned disturbance model over the experimental data used to build the other, that is, we compute the approximate representations $\tilde{\boldsymbol{\tau}}_M$ and $\tilde{\boldsymbol{\tau}}_U$ of the form:

$$\boldsymbol{\tau}_M \approx \tilde{\boldsymbol{\tau}}_M = \sum_{j=1}^{n_U} \tilde{b}_j \boldsymbol{\varphi}_j, \qquad \boldsymbol{\tau}_U \approx \tilde{\boldsymbol{\tau}}_U = \sum_{i=1}^{n_M} \tilde{a}_i \boldsymbol{\phi}_i \tag{8}$$

The estimation of the coefficients $\tilde{a}_i$ and $\tilde{b}_j$ provides a quantitative cross-information about how much $\boldsymbol{\varphi}_j$ and $\boldsymbol{\phi}_i$ are well-representative of the observed residual revolution signals. The basis $\boldsymbol{\varphi}_j$ and $\boldsymbol{\phi}_i$ for which the coefficients $\tilde{a}_i$ and $\tilde{b}_j$ exceed a certain threshold can be considered as belonging to the set of basis generating the span $\Delta\boldsymbol{\phi} \cap \Delta\boldsymbol{\varphi}$. As the basis function are already known, any standard linear regression technique can be used for the estimation of the coefficients $\tilde{a}_i$ and $\tilde{b}_j$.

At this point, the whole set of basis $\boldsymbol{\phi}_i$ and $\boldsymbol{\varphi}_j$ can be divided into three disjoints sets: the first, generating the span $\Delta\boldsymbol{\phi} \cap \Delta\boldsymbol{\varphi}^c$; the second, generating the span $\Delta\boldsymbol{\phi}^c \cap \Delta\boldsymbol{\varphi}$; the third, generating the span $\Delta\boldsymbol{\phi} \cap \Delta\boldsymbol{\varphi}$. Any residual dynamic can now be decomposed as the superposition of three distinct sources: the first, due to the unknown dynamics of the moving base link; the second, due to the unexpected collisions; the third, due to either disturbance sources. The values of associated coefficients a_i and b_j to the first two disjoint set of basis functions, respectively, allow us to determine the contribution of each kind of disturbance affecting the residual signal.

IV. Conclusions

Recently, Menna et al. [5] developed a contact sensor for ATVs based on a classifier trained with Support Vector Machines (SVM). In formal terms, this sensor extends the classical fault detection approach based on the analysis of the large variations of commanded torques/motor currents, allowing the isolation. The isolation of the fault is obtained by manual labeling of the contact signal necessary, in turn, to train the model. In contrast, the proposed approach provides both detection and isolation without relying on manual data labeling. Moreover, this approach does not require the determination of the contact points of the flippers, thus overcoming the principal methodological and practical limitations of the previous approach.

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