

DETECTING SLIP IN ROBOTIC GRASPS

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1. MOTIVATION AND INTRODUCTION

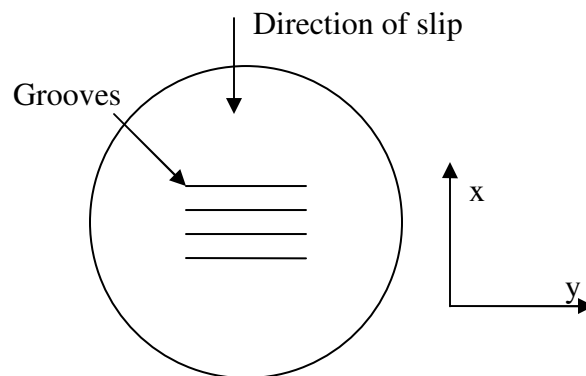
This project explores the viability of using machine learning to detect when objects are slipping through the grasp of a robotic hand. To that end, this paper discusses how one might use classification to identify when objects are sliding over the surface of a load cell that could be installed in a robotic hand. It is found that through proper feature selection, slipping loads can be distinguished from arbitrary loads using logistic regression when the axis of slip is known a priori. An approach for learning the axis of slip is also presented, which generalizes the detection scheme for slip in arbitrary, unknown directions.

2. TEST SETUP

The setup for gathering training and test examples is illustrated in Figure 1. The load cell surface is shown in the x-y plane. The z axis completes a right handed coordinate system. Slipping occurs about the x axis through the center of the load cell. To aid in slip detection, grooves have been notched along the y-axis, which induce disturbances in load cell readings as objects slide across.

Measurements from the load cell are given by the set $\{m_x, m_y, m_z, f_x, f_y, f_z\}$. Slipping training examples and test cases are generated by sliding objects down the x axis through the center of the load cell. Non-slip training examples and test cases are generated by placing arbitrary loads on the load cell. A training or test example consists of concurrent 400 point time series of each measurement, sampled at 1600 Hz.

Figure 1 – Load Cell Surface



3. FEATURE SELECTION

Through manual inspection, various slipping signatures have been identified and are summarized in Table 1.

Table 1 – Classifier Features

Feature f_n	Measurement	Slipping Signature	Rationale	Feature Mapping
n = 1	m_y	Ramp Variation	Moment arm varies linearly as load slides down x axis	Residual of least squares fit to ramp model
n = 2,3,4	f_x, f_z, m_y	Vibration	Grooves induce vibration	Energy in specific frequency band
n = 5	f_x, f_z	Common Disturbance	Grooves cause common disturbance in f_x and f_z	cov(Fx,Fz)
n = 6	m_z	Constant	Slipping along straight line does not induce torsion load	var(m_z)

The first feature accounts for the ramp variation in the moment m_y that is observed when an object slides down the x axis. This ramp variation is attributed to the linear variation in the moment arm that occurs when an object slips at a constant rate. The ramp variation is modeled by equations (1) and (2)

$$m_y(t) = f_x(t) \cdot r_z + f_z(t) \cdot r_x(t) \quad (1)$$

Where $r_x(t)$ has the linear, or ramp, variation given by

$$r_x(t) = a \cdot t + b \quad (2).$$

In vector form (1) is expressed

$$m_y(t) = k(t)^T \cdot \theta \quad (3),$$

where

$$\theta = [r_z, a, b]^T \quad (4)$$

and

$$k(t) = [f_x(t), f_z(t) \cdot t, f_z(t)]^T \quad (5).$$

The first feature of our classifier indicates how well the measured $m_y(t)$ exhibits this ramp variation for $\forall t \in \{1..400\}$. For each training or test set, this is assessed by solving a regularized least squares solution for θ and taking the residual of this least squares fit

with the actual measured $m_y(t)$'s. This residual is kept as the first feature. The least squares problem corresponds to the over determined system given by

$$M_y = K\theta + w \quad (6),$$

where $M_y \in R^{400}$, $K \in R^{400 \times 3}$, and $w \in R^{400}$. The i^{th} row of M_y corresponds to $m_y(i)$ and the i^{th} row of K corresponds to $k(i)$. w is noise distributed $N(0, \Sigma_w)$, where Σ_w is determined experimentally.

To ensure that training or test sets that do not exhibit ramp variations have a sufficiently large residual, the least squares problem posed in Equation 6 is regularized by the prior belief that θ is a random vector distributed $N(\mu_\theta, \Sigma_\theta)$, where μ_θ and Σ_θ are found using maximum likelihood estimation over the slipping training sets. This regularization can be viewed as MAP estimation of the vector θ where we condition θ on the measured m_y 's. That is, we maximize $p(M_y | \theta) \cdot p(\theta)$. The solution for this can be expressed in closed form as

$$\theta_{MAP} = (K^T \Sigma_w^{-1} K + \Sigma_\theta^{-1})^{-1} (X^T \Sigma_w^{-1} M_y + \Sigma_\theta^{-1} \mu_\theta) \quad (7).$$

Given θ_{MAP} , we then defined the first feature as

$$f_1 = (K\theta_{MAP} - M_y)^T (K\theta_{MAP} - M_y) \quad (8).$$

The 2nd, 3rd, and 4th feature contain information about the vibrations induced in the measurements f_x , f_z , and m_y by the grooves in the load cell. Vibrations are observed in f_x and f_z since the grooves disrupt motion in x and z. Vibrations are observed in m_y since m_y is partially determined by f_x and f_z . The ratio of energy stored in frequencies caused by slipping, which is experimentally determined over our training sets, versus total energy in the signal is kept as a feature. For feature 2, this is expressed as

$$f_2 = \frac{\sum_{i=1}^{200} 1\{i \in S\} DFT\{(f_x)\}_i^2}{\sum_{j=1}^{200} DFT\{(f_x)\}_j^2} \quad (9),$$

where S is the set of all indices of the DFT corresponding to frequencies excited by slipping and $1\{ \}$ is the indicator function. Note that the DFT is only 200 points long, since it has been taken without any zero padding and the redundant information for frequencies above the Nyquist rate has been discarded. For this application, the DFTs are taken using a Chebyshev window, which optimally trades leakage and smearing in the frequency domain [1]. Finally, all measurement series are normalized to be unit norm and zero mean before being transformed to the frequency domain.

Feature 5 offers another quantitative look at the grooves affect on f_z and f_x . Since the grooves simultaneously disrupt motion in the x and z direction, a non zero correlation in the measurements f_z and f_x is expected. Thus, $\text{cov}(f_x, f_z)$ is kept as the 5th feature.

Finally, the 6th and final feature captures the fact that slip should not induce perturbations in torsion load. Thus, $\text{var}(m_z)$ is kept as a feature and is expected to be small, since m_z should be constant.

4. CLASSIFICATION

By judicious feature selection, the classification problem becomes easily tractable with logistic regression. If we partition 40 training examples into 5 subsets and perform K-Fold cross validation, we find our average test error over the 5 subsets is 2.5%. The subsets are mutually exclusive over the entire set of training examples, and each contains an equal number of slip and non slip cases.

5. GENERALIZATION TO SLIP IN ARBITRARY DIRECTIONS

The problem as posed assumes the axis of slip is known a priori. This constraint can be removed by applying a coordinate transformation to the raw measurements such that slip is occurring about a single axis, which then enables direct application of the above feature mappings. We can learn this coordinate transformation from raw measurements through PCA. First, we note that slipping can only occur in the x-y plane. We then assume that when slipping takes place, it will represent the dominate dynamic loading of the load cell. We express this mathematically as

$$\hat{v} \perp \arg \max_{\hat{u}} \text{var}(m_{\hat{u}}) \quad (10),$$

i.e., the direction of slip \hat{v} is perpendicular to the axis that has the moment with the largest variance. $m_{\hat{u}}$ is therefore the 1st Principal Component of the matrix $B \in R^{400 \times 2}$ where the i^{th} row of B is given by

$$[m(i)_x - \text{mean}(m_x), m_y(i) - \text{mean}(m_y)] \quad (11).$$

The coordinate transformation of (x,y) space to (u,v) space is simply the transposed, orthogonal matrix of right singular vectors of B, found using the SVD. If we apply this coordinate transformation to the m_x, m_y, f_x, f_y measurements we are able to recast the above discussion as a general framework for detecting slip with the caveat that the load cell have concentric grooves instead of parallel grooves. This is required so that vibrations induced by slipping are independent of the slip axis.

6. CONCLUSIONS AND FURTHER WORK

Through proper feature selection, it has been shown that slipping loads can be successfully distinguished from arbitrary loads. Further work will be to expand the outlined approach to slipping in arbitrary directions, using the algorithm discussed in

Section 5. A real time implementation will also be pursued. To that end, efficiencies in the feature mappings will be explored. Examples of sought after efficiencies are minimal sampling rates of the time series data that achieve desired performance as well as fast algorithms for DFT, SVD and covariance.

REFERENCES

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