Identification of an Industrial Hybrid System

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Abstract— **In this paper we present an experimental study in the identification of an industrial hybrid system. Piecewise ARX models, that consist of a number of ARX models, together with the partition of the regressor space into regions where each of the models is valid, were identified. Effects of dry friction, and mechanical constraints in the experimental setup are demonstrated, and their influence on the identification procedure is discussed. Comparison of the simulated responses of the identified models with the responses of the real system shows that the obtained models are able to describe relevant aspects of the dynamics of the experimental setup. Ways to improve the identification procedure are proposed.**

I. Introduction

In this paper we present an experimental study in the identification of an electronic component placement process in the pick-and-place machines. Pick-and-place machines are used to automatically place electronic components on the printed circuit board (PCB), and form a key part of an automated PCB assembly line. The pick-and-place machine works as follows: PCB is placed in the working area of the mounting head; the mounting head, carrying an electronic component (using, for instance, vacuum pipette), is navigated to the position where the component should be placed on the PCB; the component is placed, released, and the process is repeated with the next component. Fast component mounter, consisting of the 12 mounting heads working in parallel is shown on picture 1. Throughput of such configuration can be up to 96.000 placed components/hour [4].

Control of the pick-and-place machine is a complex hierarchical problem. In the sequel we turn our attention to the mounting head, i.e. to the process of the component placement on the PCB. Assuming that the mounting head, carrying the component, is in the right position above the PCB, the component is pushed down, until it comes in contact with the PCB, and released. PCB is not rigid, but, depending on the material, has certain elastic properties. The whole operation should be as fast as possible (to achieve maximal throughput), while satisfying technological and safety constraints (e.g. the exerted forces must not damage the component). For the purpose of analysis, control design and simulation, models of the placement process are needed. In this paper we demonstrate that suitable models can be identified from experimental data.

Fig. 1. Fast component mounter (courtesy of Assembleon)

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During the placement process at least two different situations can be distinguished: when the component is not in contact with the PCB, and when there is a contact between the component and the PCB. There is at least one switch between this two situations. This motivates the search for the model in the area of hybrid systems. General definition and other examples of hybrid systems can be found, for instance, in [3]. Tractable methods to approach certain special subclasses of hybrid systems are developed recently: conditions for existence and uniqueness of solution trajectories for linear complementarity systems [9], stability criteria for piecewise affine systems [10],[11], control and verification techniques for MLD systems [1], identification for MLD systems [2]. Mentioned classes of systems are proved to be equivalent [8], so that transfer of techniques and results from one class of the systems to another is possible.

General identification technique for identifying discrete time hybrid systems in piecewise affine (PWA) form was developed in [6], [7]. In this paper we apply this technique to the experimental setup, made around the mounting head of the pick-and-place machine. Experimental setup is described in section II. Brief summary of the identification procedure is given in the section III. Detailed description of the identification algorithm is given in [6], [7]. Identification results and discussion are presented in section IV. Conclusions and discussion on possible improvement of the identification procedure are presented in section V.

II. Experimental setup

In order to study the placement process an experimental setup was made, as depicted on figure 2. The schematic of the setup is presented in figure 3. Setup consists of a mounting head, from the actual pick-and-place machine, which is fixed above the impacting surface (small orange disc, fig. 2). Impacting surface is in contact with the ground via the spring (spring c_2, fig. 3, within the brown tube on fig. 2), which is intended to simulate elasticity properties of the real PCB. Mechanical construction under the impacting surface is such that only movement on the vertical axis is enabled (white tube, which can slide inside the brown tube, fig. 2). This construction provides linear friction (damper d_2, fig. 3) , and dry friction (block f_2, fig. 3), as discussed later.

Mounting head contains a vacuum pipette, which can move on the vertical axis (depicted by mass M, fig. 3), which is connected with the spring to the casing (spring c_1, fig. 3), an electrical motor, which enables such movement (depicted by force $\vec{F}$, fig. 3), and a position sensor, which measures the position of the pipette, relative to the upper retracted position. Position axis is pointed downwards (i.e. the value of the position increases when the pipette moves downwards). Motion of the pipette is also subject to friction (damper d_1, dry friction block f_1, fig. 3).

Fig. 2. Experimental setup

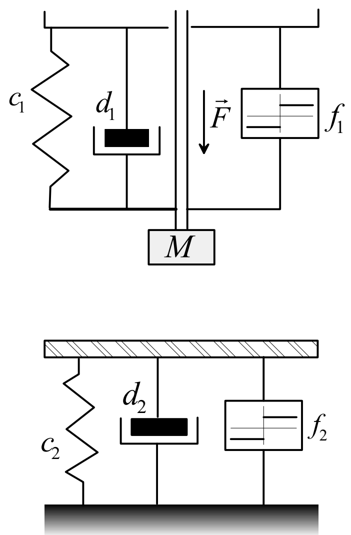

Fig. 3. Model of the mounting head

We distinguish the following situations:
1. pipette is in the upper retracted position (i.e. can not move upwards, due to the physical constraints),

hereafter referred to as upper saturation
2. pipette is not in contact with the impacting surface, but is not in the upper saturation; referred to as free mode
3. pipette is in contact with the impacting surface, but is not in lower saturation (see situation 4); referred to as impact mode
4. the spring below the impacting surface is in saturation, pipette can not move downwards due to the physical constraints; referred to as lower saturation.

Control input of the experimental setup is the voltage applied to the motor (which is, with the negligible time constant, converted to the proportional force $\vec{F}$). Input signal for the identification experiment should be chosen in a way that all modes are sufficiently excited [7]. Exact conditions that input signal should satisfy are the subject of the future research. To obtain the data for identification, input signal u is chosen as:

$$u(t) = \sum_k a_k (h(t - kT) - h(t - (k+1)T)$$

where T is a fixed time step, $h(\cdot)$ is a step signal, and the amplitude a_k is a random variable, with uniform distribution in the interval $[a, b]$. By properly choosing the boundaries of the interval $[a, b]$ only ceratin modes of the system are excited (e.g. only free and impact modes can be excited, without reaching upper and lower saturations).

Some details of the data sets obtained with this input signal are shown in figure 4. In fig. 4a an effect of dry friction damping on the system response is depicted. In fig. 4b small changes in the input signal produce no change in position (dry friction in stick phase). In fig. 4c system is excited so that lower saturation is reached. Lower saturation effectively acts as a state reset map (non-elastic impact), active when certain position is reached. In fig. 4d both upper and lower saturations were reached. Bouncing effect can be observed when reaching upper saturation, due to non-elastic impact with the constraints.

III. Identification algorithm

We consider the problem of reconstructing a Piece-Wise Affine (PWA) map from a finite number of noisy data points. A PWA map $f : \mathbb{X} \mapsto \mathbb{R}$ is defined by the equations

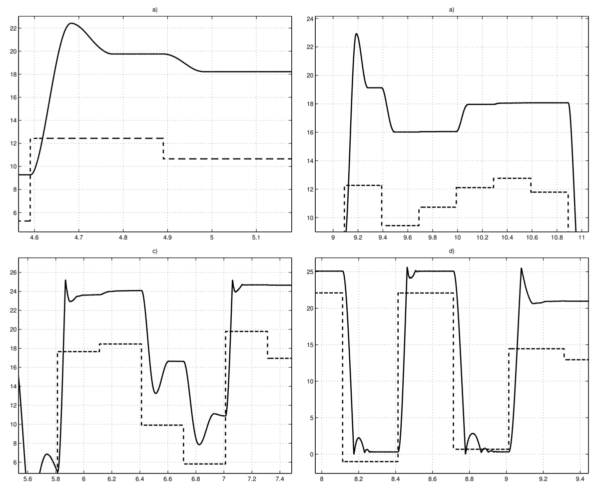

Fig. 4. Some features of the experimental data set a),b) effects of the dry friction c)lower saturation d)upper saturation (solid - system response, dashed - scaled input)

$$f(x) = f_q(x) \quad \text{if} \quad x \in \bar{\mathcal{X}}_q \tag{1}$$

$$f_q(x) = \begin{bmatrix} x^T & 1 \end{bmatrix} \bar{\theta}_q \tag{2}$$

where $\mathbb{X} \subset \mathbb{R}^n$ is a bounded polyhedron, $\{\bar{\mathcal{X}}_q\}_{q=1}^s$ is a polyhedral partition of $\mathbb{X}$ in s regions and $\bar{\theta}_q \in \mathbb{R}^{n+1}$ are Parameter Vectors (PVs). Therefore, a PWA map is composed of s affine submodels defined by the pairs $(\bar{\theta}_q, \bar{\mathcal{X}}_q)$. The data set $\mathcal{N}$ collects the samples $(x(k), y(k))$, $k = 1, \ldots, N$, generated by the model

$$y(k) = f(x(k)) + \eta(k) \tag{3}$$

where $\eta(k)$ are noise samples. We assume that the number s of submodels is known. Then, the aim of PWA regression is to estimate the PVs and the regions by using the information provided by $\mathcal{N}$.

When considering hybrid systems, an input/output description of a PWA system (see [11] for a definition) with inputs $u(k) \in \mathbb{R}^m$ and outputs $y(k) \in \mathbb{R}$ is provided by Piece-Wise ARX (PWARX) models that are defined by equation (3) where k is now the time index and the vector of regressors $x(k)$ is given by

$$x(k) = \Big[\; y(k-1) \quad y(k-2) \quad \ldots \quad y(k-n_a) \quad u^T(k-1) \quad u^T(k-2) \ldots \quad u^T(k-n_b) \; \Big]^T.$$

It is apparent that, if the orders n_a and n_b are known, the identification of a Piece-Wise ARX model amounts to a PWA regression problem.

Hereafter we summarize the identification procedure reported in [6], [7] that is structured in three steps.

1. Local Regression. For $j = 1, \dots, N$ a Local Dataset (LD) $\mathcal{C}_j$ is formed. It collects $(x(j), y(j))$ and the samples $(x, y) \in \mathcal{N}$ including the $c-1$ nearest neighbors x to $x(j)$. The cardinality c of an LD is a parameter of the algorithm satisfying $c > n+1$. LDs collecting only datapoints associated to a single submodel are referred to as *pure* LDs. Otherwise the LD is termed *mixed*. Linear regression is performed on each LD $\mathcal{C}_j$ to obtain the Local Parameter Vectors (LPVs) θ_j. The LD centers $m_j = \frac{1}{c}\sum_{(x,y)\in\mathcal{C}_j} x$ are also computed and the Feature Vectors (FVs) $\xi_j = [\theta_j', m_j']'$ are formed. As for the LDs, FVs are either pure or mixed.

Intuitively, if c and the noise are "small" enough, pure FVs (that capture characteristics of the true submodels) are expected to form s dense clouds in the FV-space whereas mixed FVs form a pattern of isolated outliers.

2. Clustering. The FVs are partitioned in s groups through clustering. For this purpose, a K-means algorithm (see [5])exploiting suitably-defined confidence measures on the FVs can be used. Confidence measures allows to assign little influence to the mixed FVs so that the clustering results mainly depend on pure FVs. The resulting clusters are denoted with $\{\mathcal{D}_q\}_{q=1}^s$.

3. Estimation of the submodels. By using the bijective maps $(x(j), y(j)) \leftrightarrow \mathcal{C}_j \leftrightarrow \theta_j$, sets $\{\mathcal{F}_i\}_{q=1}^s$ of data points are built according to the rule: $(x(j), y(j) \in \mathcal{F}_q \leftrightarrow \theta_j \in \mathcal{D}_q$. The points in each final set $\mathcal{F}_q$ are then used for estimating the PVs of each submodel through weighted least squares. The regions $\{\mathcal{X}_q\}_{q=1}^s$ are reconstructed on the basis of the final sets by resorting to multicategory pattern recognition algorithms (see [12]) that find the hyperplanes $\{x : (x, y) \in \mathcal{F}_q\}$, $\{x : (x, y) \in \mathcal{F}_{q'}\}$ for all indices $q \neq q'$.

As pointed out in [7], [6], if the signal-to-noise ratio is "high" enough, it is expected that the sets $\mathcal{F}_q$ correctly classify the largest part of the datapoints, i.e. those corresponding to pure FVs. Misclassified datapoints can be also detected and re-attributed a posteriori through residuals analysis. This will improve the overall quality of the reconstructed model.

IV. Identification with free/impact modes

In the following experiment the parameters of the input signal were chosen so that only impacts between the head and the spring occur (i.e. no upper/lower limits are reached). The obtained data-set was divided in two sets: one is used for identification, and the second is used for validation. Two sets of data, together with the scaled input signals are shown in figure 5. The effects of the friction nonlinearity are clearly observable, for instance in figure 5b, on the time interval $(175, 250)$.

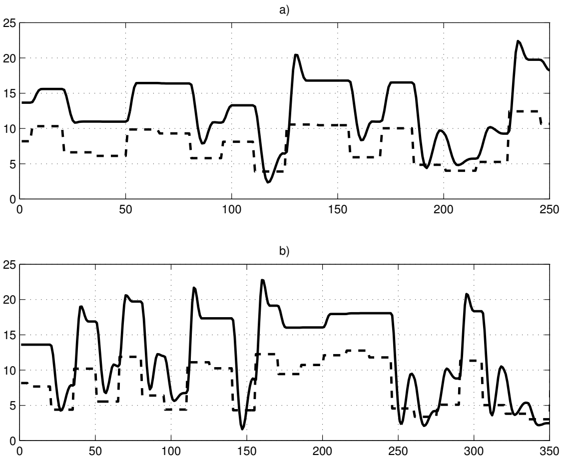

Fig. 5. Data sets used for a)identification and b)validation (solid - system response, dashed - scaled input)

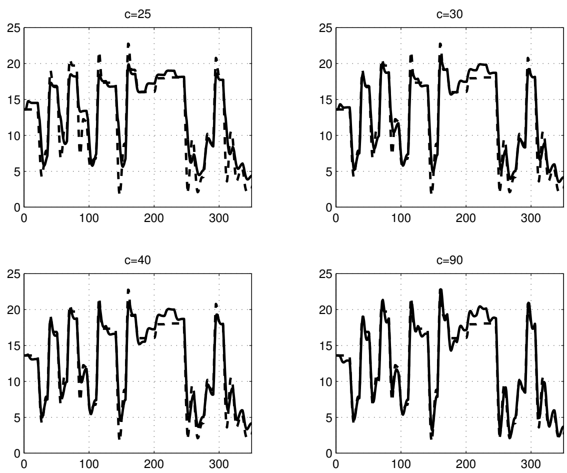

Fig. 6. Responses of the identified 2+1 models for different values of c (solid - model response, dashed-system output)

PWARX models with two modes were identified, with parameters $n_a = 2, n_b = 1$ and $n_a = 2, n_b = 2$, respectively. Results of the identification algorithm

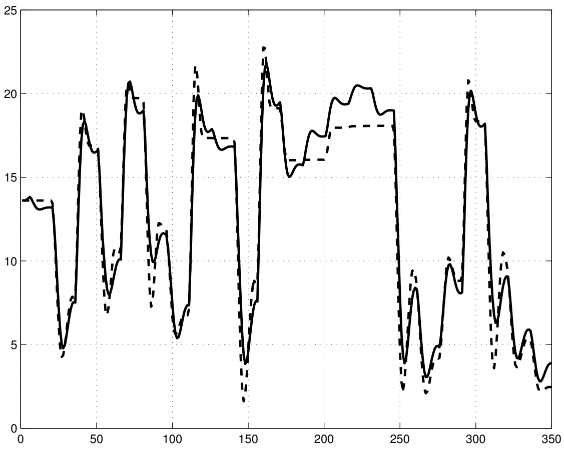

Fig. 7. Response of the identified 2+1 model, 2 modes, $c = 55$ (solid - model response, dashed-system output)

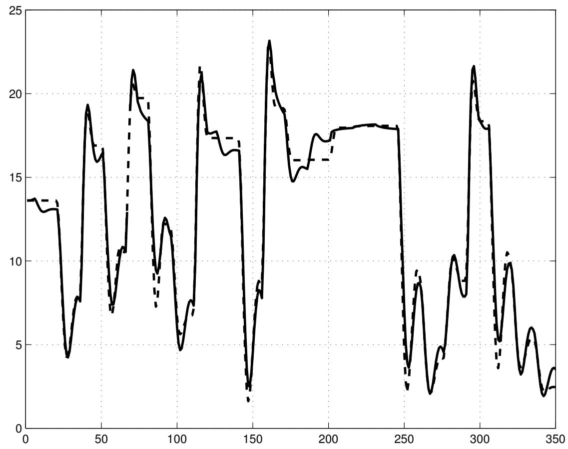

Fig. 9. Responses of the identified 2+2 model, 3 modes, $c = 35$ (solid - model response, dashed-system output)

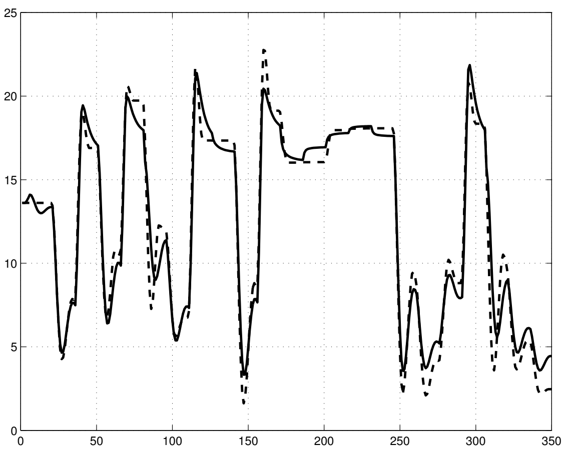

Fig. 8. Responses of the identified 2+2 model, 2 modes, $c = 55$ (solid - model response, dashed-system output)

are presented in figures 6-8. The parameter c, i.e. the size of the local data cluster in the first step of the identification algorithm, determines the quality of the obtained model. For minimal theoretical values of c ($c = 4$, resp. $c = 5$) the obtained models are not usable (i.e. predict responses that are completely dissimilar to the measured ones). Figure 6 shows the responses of the obtained (usable) models for a wide range of values of c. Obtained models differ in quality, and good models are obtained for $c \geq 40$. It is interesting to note that even for a large values of c (i.e. $c = 90$, for a data set of 250 points) good models can be obtained.

When the PWARX model with two modes is identified identification procedure makes an attempt to distinguish two major groups (clusters) of data points, and to fit an ARX model to each of them. Intuitively, this two groups correspond to the free and impact modes. Because of the presence of dry friction (see figures 4a,4b) responses in both modes are nonlinear. Therefore, local data sets (LDs) with small cardinality (small c) will produce scattered parameter estimates, and clustering will not be successful. LDs collecting large number od data points (large c) will produce a parameter estimates corresponding to the "averaged" linear model. Such parameter estimates form clusters in the parameter space. Effect of "averaging" is noticeable in figure 7, where responses to the large step signals are predicted correctly, but responses to the small step signals are incorrect (time interval $(175, 250)$), and in figure 8, where the compromise is made between responses to large and small step signals.

Previous discussion motivates the attempt to identify a piece-wise affine model with more modes, on the same data set. Result of the identification when $s = 3$ is shown in figure 9. Points on time interval $(200, 250)$ are classified as belonging to the third mode, and the predicted response is correct. Points on the interval $(150, 200)$ are classified as belonging to the other mode, and the response is not correct. Identification with more modes was not successful.

Identification with higher model orders, with two or three modes shows no significant difference on the response quality.

V. Conclusions

In this paper the identification of the experimental setup, made around the mounting head of a pick-and-place machine was discussed. Piecewise ARX (PWARX) models of the system were identified, using the methodology introduced in [7]. The obtained models can be used, for instance, for control design [1], diagnostics and fault detection.

The identified models consist of a certain number of ARX models (modes), together with the partition of the regressor space into regions where each of the models is valid. Initial parameters of the identification procedure (number of modes and model orders) can be determined for instance, by physical insight in the process to be identified. Another input parameter of the algorithm is the size of the local data cluster c, and it is demonstrated that c plays a crucial role in obtaining good models.

Nonlinear effects due to dry friction were observed in the collected experimental data, especially in the mode when the head is in contact with the spring. Effects of the friction can be "averaged out", using large local data sets, but good response prediction can not be achieved. Effects of the friction can be taken into account by allowing additional modes in the identified model. In this case special care has to be taken about the input design, in order to sufficiently excite all modes. This is the subject of the further research.

In practical situations a lot of a-priori information on the nature of the system to be identified is usually available before the identification experiment (e.g. number of modes, model orders, saturation values, correlation between certain parameters in linear models...). In the present moment only limited amount of such information can be supplied to the identification procedure. Future research will focus on the possibilities of supplying more information to the identification procedure (gray box modelling), and on determining structural models (like the one depicted in figure 3), and their parameters (white box modelling).

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