Contact-State Recognition of Compliant Motion Robots Using Expectation Maximization-Based Gaussian Mixtures

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Summary/Abstract

In this article, we address the problem of Contact-State (CS) recognition for force-controlled robotic tasks. At first, the wrench (Cartesian forces and torques) and pose (Cartesian position and orientation) signals of the manipulated object, in different Contact Formations (CFs) of a task, are collected. Then in the framework of the Bayesian classification, the Expectation Maximization-based Gaussian Mixtures Model (EM-GMM) is used in building efficient CFs classifiers. The use of the EM-GMM in developing the captured signals models accommodates possible signals non-stationarity, i.e. signals abnormal distribution, and enhanced recognition performance would be resulted. Experiments are performed on a KUKA Lightweight Robot (LWR) doing the cube-in-corner assembly task, which is a rigid cube object interacting with an environment composed of three orthogonal planes, and different CFs are considered. From the experimental results, the EM-GMM is shown to have an excellent recognition performance with an enhanced computational time. In order to compare the EM-GMM with the available CF recognition schemes, we developed the corresponding CF classifiers using the Gravitational Search-Fuzzy Clustering Algorithm (GS-FCA), Stochastic Gradient Boosting (SGB), and the Conventional Fuzzy Classifier(CFC) approaches. From the comparison, the EM-GMM scheme is shown to be outperforming the rest.

1 Introduction

Contact State (CS) monitoring is considered one of the crucial elements in transferring human skills to the force-controlled robotic tasks. It provides an abstract knowledge of the surrounding environment through employing the sensed wrench (Cartesian forces and torques), pose (Cartesian position and orientation), and/or twist (linear and angular velocities) of the manipulated object in acquiring such skills. The vitality of such skills transfer to the robots spurred the interest of researchers and practitioners from both research and industrial institutions. However, the CS recognition in the force-controlled robot systems is rooted back to the 1980s.

In [1], Desai and Volz proposed a significant milestone in transferring skills to the compliant motion robots by introducing the notion of the Contact Formation (CF). For instance, if we have a polyhedral manipulated object interacting with a certain environment, then we can describe the contact of the object vertex to the face of the environment and call it as a vertex-face *(v-f)* contact. Similarly, for edge-face *(e-f)*, face-face *(f-f)*, edge face-2faces *(ef-2f)*, 2faces-2faces *(2f-2f)*, 3faces-3faces *(3f-3f)*, and other possible contacts. Each one of those contacts phases is called a Contact Formation (CF), and a compliant motion robotic task can be composed of a set of those CFs. Hirai and Iwata proposed a CF recognition scheme for such robotic systems using the geometric model of the manipulated object along with the sensed forces [2]. Petri net was successfully employed in modeling and planning force-controlled robotic tasks and promising results were obtained [3].

In [4, 7], neural networks and fuzzy classifiers were employed in recognizing different CFs for different objects without needing the geometrical features of the manipulated object. Modeling of different contacts in robotic peg-in-hole assembly process was successfully performed in the framework of finding analytical solutions of the contact forces for different situations between the manipulated object and the environment [8]. Hidden Markov models were successfully used in developing CFs models for compliant motion robots and hence opening the door to the probabilistic modeling approaches [5, 9].

In [6, 12], the authors were successful in linking the CF modeling to the geometrical parameters estimation and efficient models were obtained for each CF. In [11], force/torque mapping for each model was developed using CAD data along with the particle filters and enhanced CF modeling was resulted. ARX modeling was successfully employed in adding the recognition skills to the peg-in-hole robotic assembly tasks and promising results were obtained [13].

Cabras *et.al.* were capable of using the Stochastic Gradient Boosting (SGB) classifier in recognizing different CFs without the need for knowing the task sequence or task graph [14]. In [16], the authors used only the force and torque vectors in recognizing different CFs for a compliant motion robots. The approach computes the wrench space automatically based on the CFs graph, which describes the sequence of different CFs in a certain task. Then, a similarity index is augmented that shows the amount of overlap between wrenches that belong to different CFs. Finally, a particle filter is used to compute the likeness that a certain wrench vector belongs to a CF. The results shown in [16] are excellent for the computational time wise, i.e. the time required for developing the models, however the sequence of the CFs is still needed to be known. In [17], the authors were successful in using fuzzy clustering technique in building efficient fuzzy models. The fuzzy clusters are tuned by Gravitational Search Algorithm (GSA) and excellent mapping capability was obtained for each model. A common feature to all of the approaches above is the lack of considering the signals non-stationary behavior, i.e. the non-normal signals distribution, which is frequently the case to many compliant robotic tasks. Such signals non-stationary behavior is expected to cause recognition performance improvement if well considered in developing the models.

In order to accommodate such non-stationary behavior of the signals, one can consider employing multiple Gaussian components instead of one and use the concept of Gaussian Mixtures Model (GMM) in building the likelihood for each signal [10]. The well-known Expectation Maximization (EM) algorithm can be used in finding the parameters of the GMM components that maximizes the log-likelihood and hence an optimal modeling for those non-stationary signals could result. Originating from such a motivation, this article proposes the use of the Expectation Maximization-based Gaussian Mixtures Model (EM-GMM) in the CF recognition of compliant motion robotic tasks. The captured wrench and pose signals, of a task, are firstly segmented according to their corresponding CFs and then the EM-GMM is used in building models that efficiently maps the CFs to their corresponding signals. Experimental validation is carried out on a KUKA Lightweight Robot (LWR) doing a cube-in-corner assembly task which is composed of a rigid cube interacting with three orthogonal planes. A task composed of seven distinct CFs is considered and a model is developed for each CF using the EM-GMM scheme. The considered CFs are free space *(fs)*, vertex-face *(v-f)*, edge-face *(e-f)*, face-face *(f-f)*, edge face-2faces *(ef-2f)*, 2faces-2faces *(2f-2f)*, and 3faces-3faces *(3f-3f)*. The task flows as follows: *(fs)-(v-f)-(fs)-(e-f)-(fs)-(f-f)-(ef-2f)-(2f-2f)-(3f-3f)-(fs)*. Excellent CF recognition performance is obtained when using the EM-GMM in recognizing such a robotic task. For comparison purposes, we developed the corresponding CFs models for the considered experiment using the available CF recognition schemes, like the Conventional Fuzzy Classifier (CFC) [7], the SGB classifier [14], and the GS-FCA classifier [17] and the superiority of the EM-GMM CF recognition scheme is shown. In order to show that the suggested recognition scheme is not depending on the task sequence, we used the developed CFs classifiers in recognizing another task of different sequence, more specifically with sequence of *(fs)-(f-f)-(2f-2f)-(f-f)-(fs)* and the robustness against task sequence change is shown.

The rest of the paper is organized as follows; section 2 describes the CF recognition problem in compliant motion robotic tasks and section 3 explains the EM-GMM classification process. Experimental validation is explained in section 4 and section 5 presents the concluding remarks and recommendations for future works.

2 Problem Description

Consider the robotic system shown in Figure 1. This system is composed of a KUKA LWR manipulating a rigid cube that interacts with an environment of three orthogonal planes. If one drives the robot to assemble the cube in the corner, different possible CFs could be generated as the task is executed. In order to model those CFs, the overall motion is segmented according to the corresponding CFs. For each segment, the wrench and pose signals are collected and the models, that realize the desired input-output mapping, are developed. The wrench signals, of the manipulated object, are described as:

$$w = [f_x, f_y, f_z, \tau_x, \tau_y, \tau_z] \tag{1}$$

Where f_x, f_y, and f_z are the Cartesian forces and τ_x, τ_y, and τ_z are the torques around the Cartesian axes both measured for the manipulated object. Likewise to the pose of the manipulated object, it can be written as:

$$\beta = [x, y, z, \Psi_x, \Psi_y, \Psi_z] \tag{2}$$

with x, y, and z are the Cartesian position and Ψ_x, Ψ_y, and Ψ_z are the orientation around the Cartesian axes of the manipulated object. Hence, one would have 12 input signals for the mapping, say $x_k = [x_{1,k}, x_{2,k}, ..., x_{12,k}]$ with k is the sample index. In the framework of classification, one can realize such a mapping and formulate it as a CF classification problem. That is:

$$y_k = \begin{cases} 1 & \text{if } (x_k \in \text{current CF}) \\ 0 & \text{Otherwise} \end{cases} \tag{3}$$

y_k is the output of the CF classifier. It can be seen that (3) represents a nonlinear mapping between x_k and y_k and the goal of almost all modeling and classification researches is to approximate or realize this mapping as accurate as possible. The next section explains the methodology that will be used throughout this paper in realizing (3).

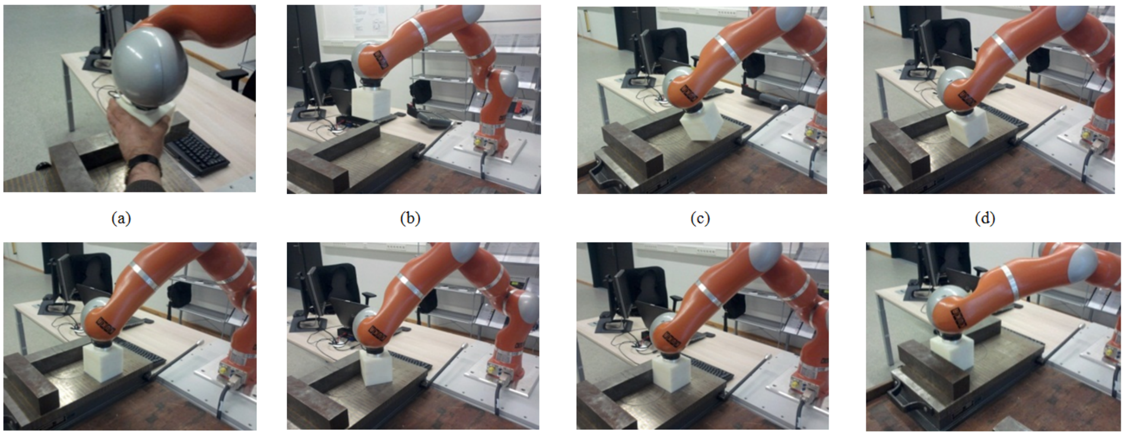
3 Expectation Maximization-based Gaussian Mixtures Model (EM-GMM)

Before explaining the EM-GMM process, the principles of the Bayesian modeling (or classification) will be clarified.

3.1 Bayesian Classification

Suppose that one is given the data vector $\boldsymbol{x}_k = [x_{k,1}, x_{k,2}, ..., x_{k,D}]^T$ where D is the width of the vector (in the CF recognition addressed in this paper, $D = 12$ that means each model has 12 inputs). Suppose that the vector $\boldsymbol{x}_k$ belongs to one of the classes $[c_1, c_2, ..., c_C]$. Through the Bayesian classification, one can say that the vector $\boldsymbol{x}_k$ belongs to a class c_i implies that [10]:

$$p(c_i|\boldsymbol{x}_k) \geq p(c_j|\boldsymbol{x}_k) \tag{4}$$



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 1: Cube-in-corner assembly task: (a) skills are added by human guidance. (b) free space *(fs)* CF. (c) vertex-face *(v-f)* CF. (d) edge-face *(e-f)* CF. (e) face-face *(f-f)* CF. (f) edge face-2faces *(ef-2f)* CF. (g) 2faces-2faces *(2f-2f)* CF. (h) 3faces-3faces *(3f-3f)* CF.

for $i \neq j$. $p(c_k|\boldsymbol{x}_k)$ is called the a posterior probability of class c_k given the vector $\boldsymbol{x}_k$ and can be computed using the Bayes rule as:

$$p(c_i|\boldsymbol{x}_k) = \frac{p(\boldsymbol{x}_k|c_i)p(c_i)}{p(\boldsymbol{x}_k)} \tag{5}$$

where $p(\boldsymbol{x}_k|c_i)$ is the probability density function (pdf) of class c_i in the vector space of $\boldsymbol{x}_k$, $p(c_i)$ is the a priori probability that represents the probability of class c_i, and $p(\boldsymbol{x}_k)$ is the probability of the vector space $\boldsymbol{x}_k$ that can be expressed as:

$$p(\boldsymbol{x}_k) = \sum_{i=1}^{C} p(\boldsymbol{x}_k|c_i)p(c_i) \tag{6}$$

From (6), one can notice that for equal class a priori $p(c_i)$, the term $p(\boldsymbol{x}_k)$ of (5) would be merely a scaling factor. Therefore, it can be deduced that the vector $\boldsymbol{x}_k$ belongs to a class c_i implies that:

$$p(\boldsymbol{x}_k|c_i)p(c_i) \geq p(\boldsymbol{x}_k|c_j)p(c_j) \tag{7}$$

for $i \neq j$. Therefore, the best approximation of the term $p(\boldsymbol{x}_k|c_j)$ results in the best classification for the pattern $\boldsymbol{x}_k$. In the conventional Bayesian classifier, a Gaussian distribution is used in approximating the term $p(\boldsymbol{x}_k|c_j)$, that is:

$$p(\boldsymbol{x}_k|c_i) = \frac{1}{(2\pi)^{D/2}|\Sigma|^{\frac{1}{2}}} exp(-\frac{1}{2}(\boldsymbol{x}_k - \mu)^T \Sigma^{-1}(\boldsymbol{x}_k - \mu)) \tag{8}$$

where $\mu \in R^D$ is the mean, $\Sigma \in R^{D \times D}$ is the covariance matrix, and $|\Sigma|$ is the determinant of Σ. It was shown that the approximation (8) performs well in the case of signals normal distribution. However in many cases, one may face situations in which the vector space signals, or several signals of the vector space, have non-normal distribution and consequently the use of (8) would result in increased modeling errors.

3.2 Gaussian Mixtures Model (GMM)

In order to accommodate the possible non-normal distribution of the signals, Gaussian mixtures is employed in modeling the features (input signals), i.e. assigning more than a Gaussian component for each feature. Suppose that a single Gaussian distribution is represented as:

$$N(\boldsymbol{x}_k, \mu, \Sigma) = \frac{1}{|2\pi|^{D/2}|\Sigma|^{\frac{1}{2}}} exp(-\frac{1}{2}(\boldsymbol{x}_k - \mu)^T \Sigma^{-1}(\boldsymbol{x}_k - \mu)) \tag{9}$$

Then a Gaussian Mixtures Model (GMM) can be described as:

$$p(\boldsymbol{x}_k|c_i) = \sum_{q=1}^{M} \omega_q N_q(\boldsymbol{x}_k, \mu_q, \Sigma_q) \tag{10}$$

M is the total number of the Gaussian mixtures, ω_q, μ_q, and Σ_q are the weight, mean, and covariance of the q^{th} Gaussian component. Suppose that $\theta_q = (\omega_q, \mu_q, \Sigma_q)$ and consider the parameter vector $\theta = [\theta_1, \theta_2, ..., \theta_M]^T$. It is clear that finding the values of the parameters is very important in having a precise modeling of the given features. Therefore, one can write the model of (10) in terms of the parameters θ as:

$$p(\boldsymbol{x}_k|c_i; \theta) = \sum_{q=1}^{M} \omega_q N_q(\boldsymbol{x}_k, \mu_q, \Sigma_q) \tag{11}$$

Finding the parameter vector θ that optimizes the models from the available measurements would enhance the performance of the classification process.

3.3 Expectation Maximization (EM)

One of the most efficient approaches in finding those parameters is the Expectation Maximization (EM) algorithm. The EM algorithm is composed of two steps; the E-step in which the log-likelihood is estimated for the current parameters, and the M-step in which the parameter θ is updated such that a maximized log-likelihood would result. In order to explain the EM algorithm, let's consider the overall data $X = [\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_N]^T$, then the log-likelihood can be computed as:

$$L(\boldsymbol{x};\theta) = \sum_{n=1}^{N} \ln(p(x_n;\theta)) \tag{12}$$

The parameter θ that maximizes (12) can be described as:

$$\theta(t) = \arg\max_\theta L(\boldsymbol{x};\theta(t)) \tag{13}$$

subject to:

$$\sum_{q=1}^{M} \omega_q = 1$$

(13) is a constrained optimization problem and the analytical solutions can be intractable. Therefore, iterative solutions, like the EM algorithm, were suggested to solve such a problem. An important quantity that plays a vital role in the EM algorithm is the conditional probability of y given **x** and let's denote $p(c_i = 1|x_k)$ as $\gamma(c_{ik})$. The value of $\gamma(c_{ik})$ can be computed using Bayes rule as:

$$\gamma(c_{ik}) = \frac{p(c_i = 1)p(x_k|c_i = 1)}{\sum_{j=1}^{M} p(c_j = 1)p(x_k|z_j = 1)} \tag{14}$$

that leads to:

$$\gamma(c_{ik}) = \frac{w_i N_i(x_k, \mu_i, \Sigma_i)}{\sum_{j=1}^{M} w_j N_j(x_k, \mu_j, \Sigma_j)} \tag{15}$$

$\gamma(c_{ik})$ is called the responsibility that the i^{th} component takes for explaining x_k [10]. The steps below summarizes the EM algorithm:
Step 1: Initialize the parameter vector $\theta_i = (\omega_i, \mu_i, \Sigma_i)$. Initialize the convergence parameters ε and ϵ.
Step 2: (E-Step) For the current parameter vector θ_i compute the responsibilities using (15).
Step 3: (M-Step) Re-estimate the parameters using the current responsibilities:

$$\mu_i^{new} = \frac{1}{N_i} \sum_{n=1}^{N} \gamma(c_{in}) x_n \tag{16}$$

$$\Sigma_i^{new} = \frac{1}{N_i} \sum_{n=1}^{N} \gamma(c_{in})(x_n - \mu_i^{new})(x_n - \mu_i^{new})^T \tag{17}$$

$$\omega_i^{new} = \frac{N_i}{N} \tag{18}$$

with:

$$N_i = \sum_{n=1}^{N} \gamma(c_{in}) \tag{19}$$

Step 4: Compute the log-likelihood:

$$\ln p(X;\theta) = \sum_{n=1}^{N} \ln\{\sum_{i=1}^{M} \omega_i N(x_n, \theta)\} \tag{20}$$

Step 5: Check for the convergence:
If $|\theta^{new} - \theta| \le \varepsilon$ or $|\ln p(X;\theta^{new}) - \ln p(X;\theta)| \le \epsilon$ then stop. Otherwise, go to **Step 2**.
See ([10]: chapter 9) for more details on the EM-GMM algorithm and the derivations of the equations above. The EM-GMM is used in building the likelihood of each signal for all CFs, and a classifier is developed for each CF in the framework of Bayesian classification. The non-stationary behavior of the wrench and pose signals is accommodated that would enhance the recognition performance.

4 Experimental Results

The test stand shown in Figure 1 was used in evaluating the performance of the EM-GMM CF recognition scheme. The key features of the KUKA LWR is detailed in [15]. The KUKA LWR is equipped with appropriate sensors that enable researchers in capturing the wrench and pose signals of the manipulated object through a Fast Research Interface (FRI) port which is installed within the robot hardware. The FRI port is connected to a remote PC that performs the computational aspects of the modeling process. The features of the PC that we used in our experiments are: Intel (R) Core (TM) i5-2540 CPU with 2.6 GHz speed and 4 GB RAM running under a Linux environment. The rate of the communication between the remote PC and the robot, through the FRI, is 100 Hz. The programming is done through a C++ platform.
For Figure 1, the robot is programmed to move from free space to the constrained phase with different CFs until it settles the cube in the corner and then back again to free space. More specifically, the overall task results in the following CFs flow: *(fs)-(v-f)-(fs)-(e-f)-(fs)-(f-f)-(ef-2f)-(f-f)-(2f-2f)-(3f-3f)-(f-f)-(fs)*. Figure 2 shows the captured wrench and pose signals for the overall task. We segmented the signals of Figure 2 according to their CFs and an EM-GMM CF classifier was developed, depending on the signals, for each CF. We used three Gaussian Mixtures for the likelihood of each signal. In order to evaluate the performance of the EM-GMM models that were developed, we repeated the experiment above and recaptured the wrench and pose signals and we obtained the signals shown in Figure 3. We used the signals of Figure 3 as inputs to the models developed in the training phase. We assumed that the winner model for each sample is the one with the highest output. Then the outputs for the EM-GMM CF classifiers is graphed

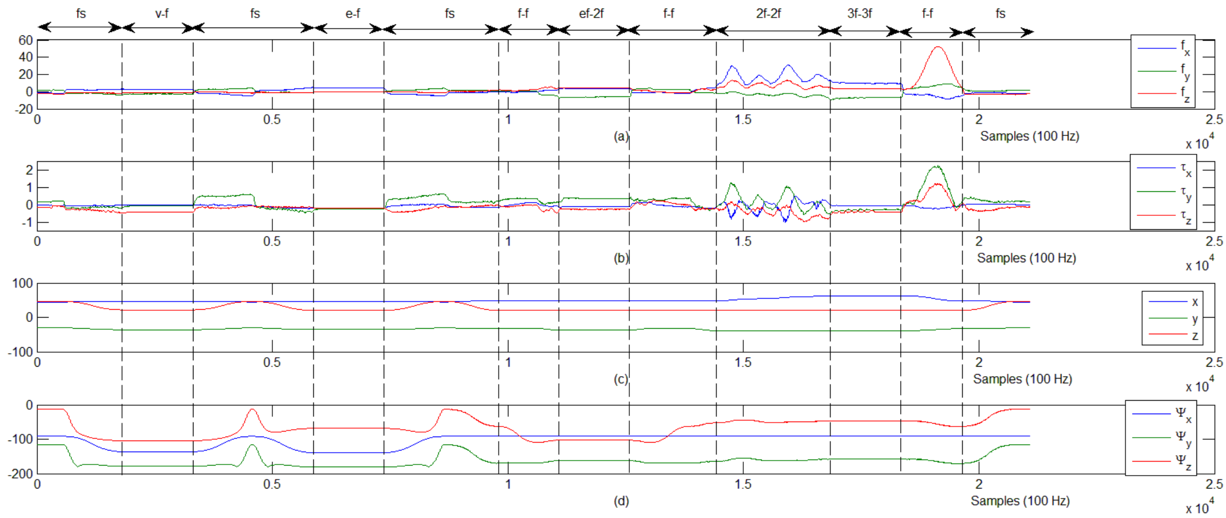


Figure 2: The training signals (a) forces along the Cartesian axes (in N). (b) torques around the Cartesian axes (in N.m). (c) Cartesian position (in cm) (d) orientation around the Cartesian axes (in degree).

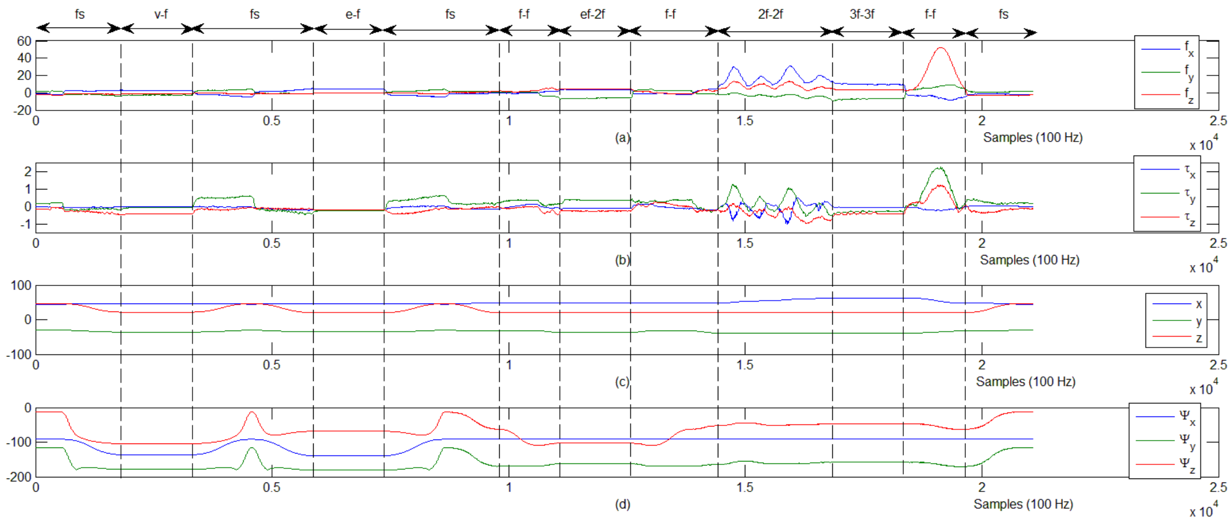


Figure 3: The test signals (a) forces along the Cartesian axes (in N). (b) torques around the Cartesian axes (in N.m). (c) Cartesian position (in cm) (d) orientation around the Cartesian axes (in degree).

and as shown in Figure 4. We can see that the EM-GMM CF modeling scheme is resulting in an excellent recognition performance with 95.1% of Classification Success Rate (CSR). For the sake of comparison, we developed the corresponding models using the Gravitational Search-Fuzzy Clustering Algorithm (GS-FCA) [17], the Stochastic Gradient Boosting (SGB) [14], and the Conventional Fuzzy Classifier (CFC) [7] and their corresponding CSR was computed to be 92.4%, 81.2% and 38.5% respectively. **Table 1** summarizes the CSR for all the approaches mentioned above.

Approach	Classification Success Rate (%)
EM-GMM	95.1
GS-FCA	92.4
SGB	81.2
CFC	38.5

Table 1: Classification Success Rate for EM-GMM, GS-FCA, SGB, and CFC CF recognition approaches.

Approach	Computational Time (sec)
CFC	0.003
EM-GMM	55.384
SGB	270.088
GS-FCA	692.758

Table 2: Computational time for EM-GMM, GS-FCA, SGB, and CFC CF recognition approaches.

Comparing the performance of the EM-GMM with the rest, we can see that the EM-GMM CF recognition scheme is outperforming the rest. The main two reasons behind such superiority of the EM-GMM scheme are the accommodation of the non-stationary behavior

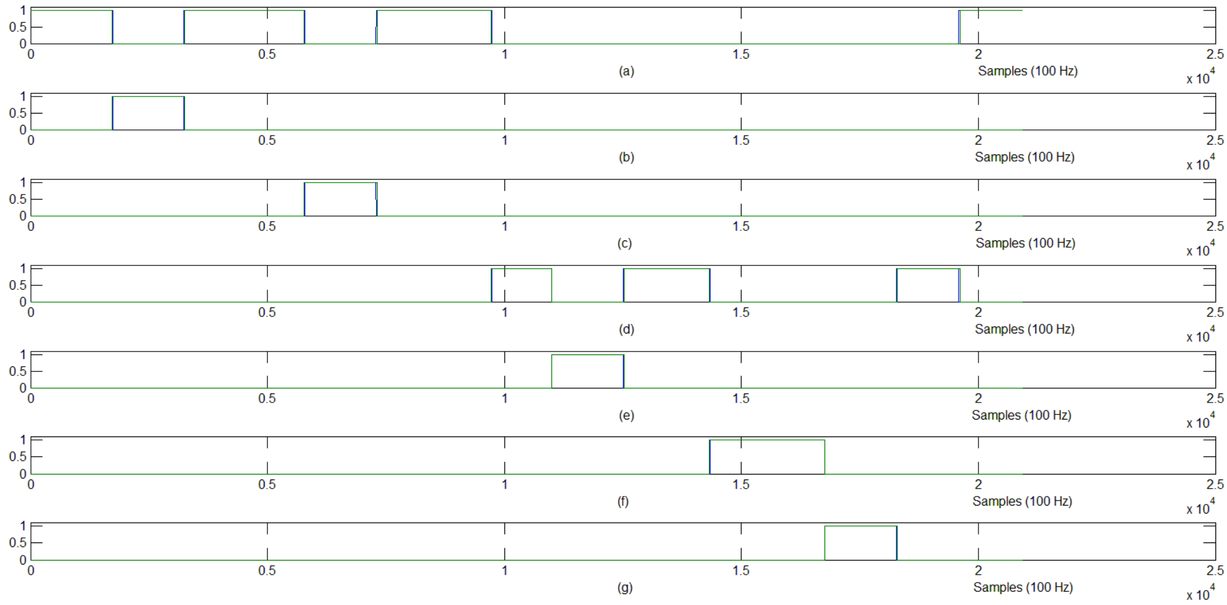


Figure 4: CFs desired (grean) and EM-GMM models outputs (blue): (a) free space *(fs)* CF. (b) vertex-face *(v-f)* CF. (c) edge-face *(e-f)* CF. (d) face-face *(f-f)* CF. (e) edge face- 2faces *(ef-2f)* CF. (f) 2faces-2faces *(2f-2f)* CF. (g) 3faces-3faces *(3f-3f)* CF.

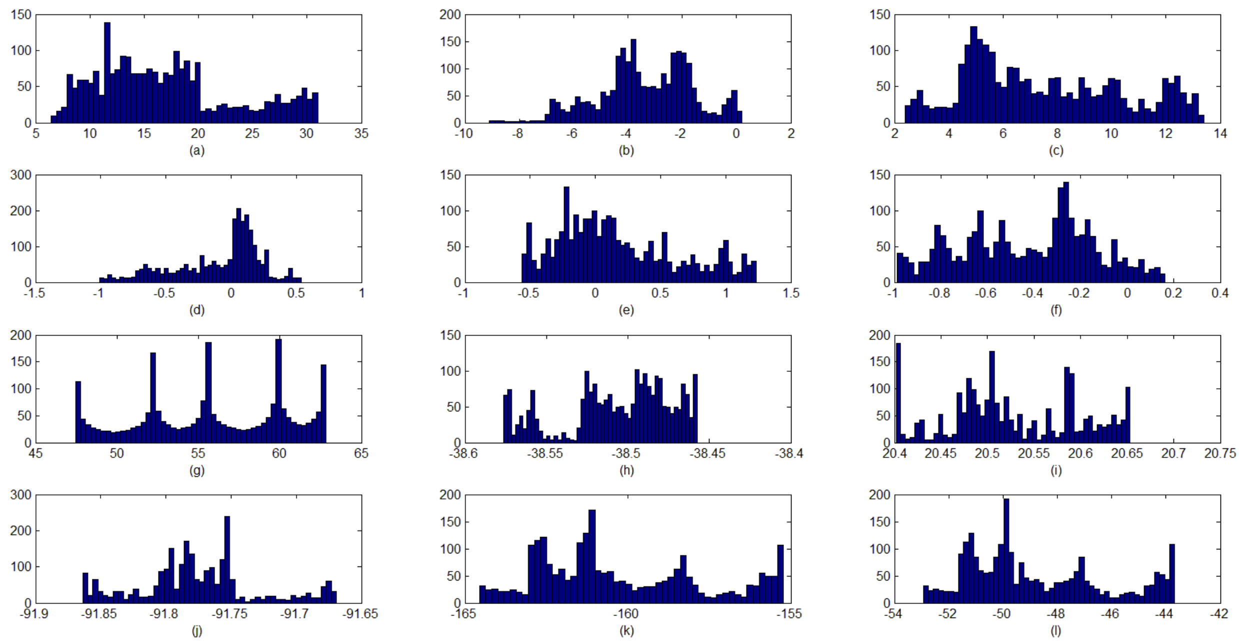


Figure 5: Histograms of the *2f-2f* CF: (a) f_x; (b) f_y; (c) f_z; (d) τ_x; (e) τ_y; (f) τ_z; (g) x; (h) y; (i) z; (j) Ψ_x; (k) Ψ_y; (l) Ψ_z.

of the signals through the use of GMM in building the likelihood functions and using the EM in computing the GMM components such that the log-likelihood is maximized. In order to see the non-stationary nature of the captured signals, we took the *2f-2f* CF as a sample and sketched the histogram for all signals of the training set of this CF. Figure 5 shows the signals histograms of the *2f-2f* CF. We can see that almost all signals have non-normal distribution, i.e. non-stationary behavior. Therefore, the use of the EM-GMM results in optimal likelihoods for the underlying signals that would significantly enhance the performance of the suggested CF recognition approach. The computational time of developing the models was also measured so that we can have a good evaluation of the computational costs. For the CFC recognition approach proposed in [7], the computational time was measured to be 0.003 sec. Whereas the computational time of the EM-GMM, SGB, and GS-FCA were measured to be 55.384 sec, 270.088 sec, and 692.758 sec respectively. The computational time of all approaches are summarized in **Table 2**, and from this table one can see that the CFC recognition scheme is having the least

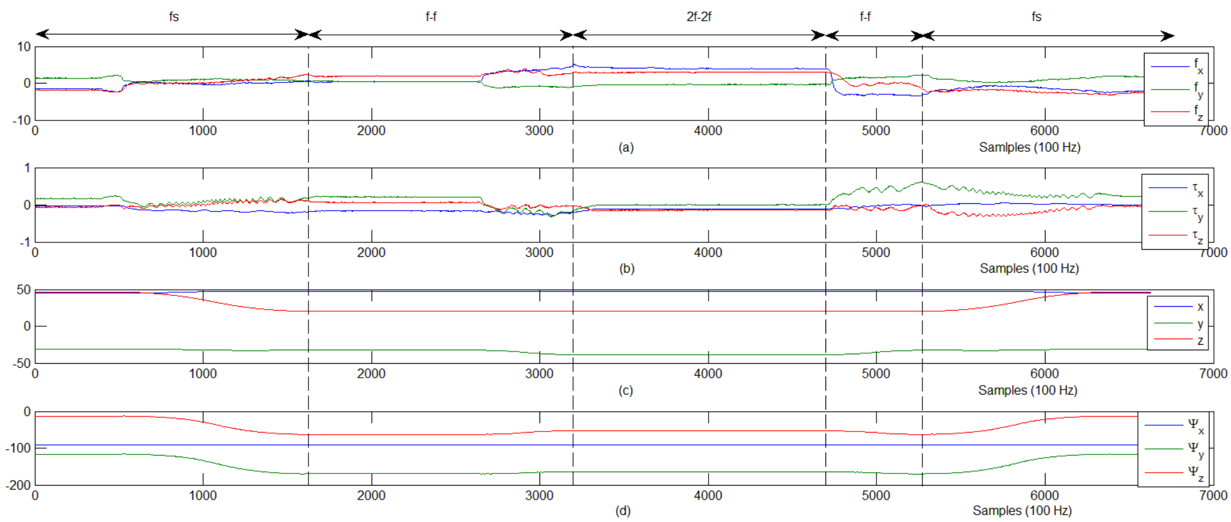


Figure 6: The second task signals (a) forces along the Cartesian axes (in N). (b) torques around the Cartesian axes (in N.m). (c) Cartesian position (in cm) (d) orientation around the Cartesian axes (in degree).

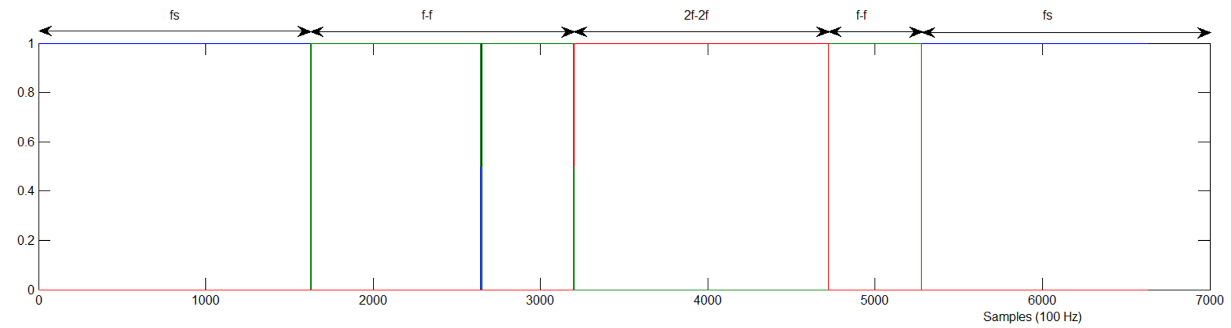


Figure 7: The CFs models for the second test task of of sequence *(fs)-(f-f)-(2f-2f)-(f-f)-(fs)* CFs .

computational cost. However, the degraded performance of the CFC recognition scheme of 38.5% is a major drawback that makes it undesirable. Compared with the GS-FCA and SGB approaches, the EM-GMM CF recognition scheme is having the least computational time along with the highest CSR. Therefore, one can say that the EM-GMM is of an enhanced performance in both accuracy and computational cost. Furthermore, in order to show that the EM-GMM is independent of the task sequence, we used the developed models for recognizing another task of sequence *(fs)-(f-f)-(2f-2f)-(f-f)-(fs)*. Figure 6 shows the wrench and pose signals for the second task and Figure 7 shows the EM-GMM CF classifiers outputs. We can see that the EM-GMM CF recognition performance is robust against the CFs sequence change and hence there is no need to know the task sequence.

5 Conclusion

In the framework of Bayesian classification, Expectation Maximization-based Gaussian Mixtures Models (EM-GMM) was successfully employed in building an efficient Contact Formations (CFs) classifiers for force-controlled robotic tasks. Using the wrench (Cartesian forces and torques) and pose (Cartesian position and orientation) signals of the manipulated object, a model was developed for each CF using the EM-GMM and an enhanced CF recognition process was obtained. The enhancement of the CF recognition stems from using the GMM in building the likelihood of the captured signals that would accommodate the non-stationary behavior of those signals and using the EM algorithm in computing the parameters of the GMM components that maximizes the log-likelihood. In order to evaluate the performance of the EM-GMM CF recognition scheme, a test stand was installed that is composed of a KUKA Lightweight Robot (LWR) doing the cube-in-corner assembly which is a rigid cube object that interacts with an environment composed of three orthogonal planes. During the task execution, seven distinct CFs are brought about. It was shown that the EM-GMM CF recognition is having an excellent performance of 95.1% Classification Success Rate (CSR). The available CF recognition schemes, like Gravitational Search-Fuzzy Clustering Algorithm (GS-FCA), the Stochastic Gradient Boosting (SGB), and the Conventional Fuzzy Classifier (CFC), were also implemented and they had CSR of 92.4%, 81.2%, and 38.5% respectively. Furthermore, we measured the computational time of developing the models and it was shown that the EM-GMM is having a moderate and reasonable computational time compared with the GS-FCA and SGB schemes. In order to show that the EM-GMM models are task sequence independent, we used the developed models in recognizing another task of a different sequence and it was shown that the suggested CF recognition performance is robust against task sequence change. Despite the excellent recognition problem of the EM-GMM approach, it requires the specification of the number of mixtures for each signal that might be difficult to be found. Therefore, future works should focus on relaxing the need for knowing the number of Gaussian components for each signal.

6 Acknowledgement

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