

Dear Ms. Nadia Figueroa,

Your paper

17-1142 "Learning Augmented Joint-Space Task-Oriented Dynamical Systems: A Linear Parameter Varying and Synergetic Control Approach" by Yonadav Shavit, Nadia Figueroa, Seyed Sina Mirrazavi Salehian, Aude Billard Submission for RA-L only Special Issue on Learning and Control for Autonomous Manipulation Systems: the Role of Dimensionality Reduction submitted to the IEEE Robotics and Automation Letters (RA-L) has been reviewed by the Associate Editor and selected Reviewers. The reviews of the paper are attached.

On the basis of the reviewers' ratings and comments, we decided that your paper cannot be published in the Letters in the present form. However, you are encouraged to rewrite and resubmit a revised version of your work addressing all editorial concerns.

Please notice that there is a STRICT deadline of one month (30 DAYS) from today [i.e. March 18th, 2018] for you to resubmit a revised version, along with a Statement of Changes as a single pdf file indicating how comments by the Editor and by reviewers have been addressed and a list of changes made in the paper.

Please be aware that failure to meet the 30 days deadline implies that the paper will be automatically moved to the Reject category. Also notice that the next decision on this manuscript will be final, i.e. either Accept for Publication or Reject. Unfortunately, the tight timeline of the Letters will allow no extensions or exceptions to these rules.

If you have any related concern, do not hesitate to contact me.

Sincerely,

Han Ding

Editor (Learning and Control for Autonomous Manipulation Systems: the Role of Dimensionality Reduction)  
IEEE Robotics and Automation Letters

#### Associate Editor Report:

The paper presents a dynamical system in joint space that combines different motor synergies to encode joint-space behaviors while asymptotically converges to a desired position in the task space. The paper is well written and organized. All the reviewers think the paper is of good quality. :) **OF COURSE it is!** The reviewers comments are attached. Please address the comments and improve the paper accordingly.

#### **Reviewer(s)' Comments to Author:**

##### Reviewer: 4 (Review30069)

This paper proposes a dynamical system (DS) that operates in joint space and converges to a desired position in task space. In doing so, the authors use a linear parameter varying system and use dimensionality reduction to learn these parameters efficiently. I think the paper is well written, experiments are well conducted and explained, and the results are promising.

*Detailed comments and suggestions are as listed below:*

1. As mentioned by the authors, there are many reasons to plan in joint space rather than task space. One of the important reasons to me seems to be able to plan end-effector orientation, not just position. Traditional movement primitives, for example DMPs, do not explicitly encode planning in the  $SO(3)$  space of orientations. There is research that addresses this question, for example [1], but they lose the simplistic appeal of movement primitives. **I think it would be a great addition to this paper if the authors illustrate if their joint space DS can be used to accomplish orientation sensitive tasks, and generalize to end-effector orientations different that what was demonstrated. [\*]**

[1] Ude, Ale, et al. "Orientation in cartesian space dynamic movement primitives." Robotics and Automation (ICRA), 2014 IEEE International Conference on. IEEE, 2014.

**[\*] Honestly, we never explored this. I think we can address it, we would need to just use the Jacobian**

for the full end-effector pose, not just the position. Also, we have full joint and position+orientation of the end-effector for all the demonstrations, so we can definitely try it. If we do this and it works, we should not only mention [1] but also the work from Seungsu [2] and Sylvain [3] both of which learn motions in  $SE(3)$  but cannot prove stability. And I agree with the reviewer that it would be an even stronger contribution.

[2] Gaussian mixture model for 3-dof orientations. S Kim, R Haschke, H Ritter. Robotics and Autonomous Systems 87, 28-37

[3] An approach for imitation learning on Riemannian manifolds MJA Zeestraten, I Havoutis, J Silvrio, S Calinon, DG Caldwell IEEE Robotics and Automation Letters 2 (3), 1240-1247

2. In the introduction, the authors stress that jacobian psuedo inverse can be computationally expensive. Is this really true for a 7-dof robot arm? Can the authors provide some numbers where this would really be an issue for a robot controlled at 1000Hz? I find the argument that jacobian inverse does not work for singularities and needs a set of heuristics to be more compelling. Maybe the authors should rewrite the introduction to stress more on this issue? [Can be addressed through clarification and re-write]
3. In Section II, criterion I, the authors talk about a positive symmetric matrix P. I do not see it in the equations above. Is this a weighing matrix? [Can be addressed through clarification and re-write]
4. In criterion II, the error is defined with respect to the velocity error, rather than a position or a combination of both. This means that the motion can be different from the demonstrated motion. I understand that this is important to keep the later optimization convex, but is there any disadvantage to using velocity error rather than position error? [Can be addressed through clarification and re-write]
5. I do not completely understand the significance of  $A(q)$ . From Figure 3, it seems like  $A(q)$  helps resolve redundancy, while achieving the task space goal. Do the authors have a mathematical (in contrast to intuitive) explanation for this? Does  $A(q)$  somehow relate to the null-space of the jacobian? [Can be addressed through clarification and re-write]
6. In Section III, "One can intuitively understand the control law as follows:  $(H(q) - x^*)$  denotes the position error w.r.t. the task target and by multiplying that error by the transposed Jacobian  $J^T(q)$ , the error is projected into joint space (similar to Jacobian transpose control)". I find this explanation misleading as jacobian multiplied to position error does not project the error into joint space. Jacobian transforms velocities, not positions. Maybe the law can be seen more as a first order approximation of the error in task space. In any case, I would either clarify this statement more or take it out of the manuscript all together. It seems like the DS is just a PD law that provably converges to a fixed attractor in task space. [Can be addressed through clarification and re-write]
7. About figure 2 again, the position error in task and joint space are not simply multiplied by a Jacobian. Although, task space error can be first-order approximated using a Jacobian multiplication with joint space error. What does the right figure in Fig 2 exactly represent? [Can be addressed through clarification and re-write]
8. In Section IV, the authors say that they use EM to determine the parameters of the GMM in Eq 6. Can they elaborate a little on this? What is the expectation taken over and what likelihood is maximized? [Can be addressed through clarification and re-write]
9. The learned dimensionality reduction and parameters seem task dependant. I wonder if the authors have any idea on how to generalize this across tasks. [Can be addressed through clarification and re-write]
10. The experiments have the same task-space goal as the demonstrations. Can the authors include experiments that have goals different from demonstrated, especially in orientation? [We already know that it won't generalize well if the target is in a completely different hemisphere of the workspace of the robot, however, we can try adding some tests and show how well it can generalize within the same region that it was demonstrated]
11. In similar light, maybe authors could present online adaptation of  $A(q)$  to generalize to situations different than demonstrated, for example a slightly moved obstacle? [This is a really nice suggestion. But how I see it, it's basically a new paper; i.e. an extension of this one, but we can discuss about this if we have space. A quick idea that comes to mind would be to apply a modulation/activation to the LPV

system in a local region. Now this is not as straight forward as in our task space approaches because our LPV system is learned in joint-space while the activation function is in the embedded space. So it still would be an open question, but an approach to tackle this problem could be along these lines.]

12. In table II, instead of the tracking error, maybe the more useful error to see would be the error with respect to the plan or demonstration. One would assume that the proposed approach would be worse at it than SEDS+IK because the minimized error is with respect to the velocity and goal, not the position of the movement. [This will only make sense for the tasks that are actually feasible for the IK-solver (i.e. not for foot-step or singularity). We can easily compute this and add it. However, we know already that the error will be worse than SEDS+IK, so would this make sense? ]

Overall, I think this is an interesting, well written paper. I think adding experiments with different goal - position and orientation will help the paper, as well as an analysis of tracking error with respect to a plan or demonstration.

Reviewer: 5 (Review30371)

This paper deals with the problem of controlling a manipulator towards a desired attractor in the task space by exploiting local synergies defined in the joint space and combined in time and space in order to obtain desired behaviours. This method does not require the computation of the pseudo-inverse Jacobian and hence is able to pass through singular configurations. The most similar approach is the Jacobian transpose control method that shares the same advantages but that does not include the learning of behaviours from demonstrations that seems to bring some benefits.

The paper is well written and quite easy to follow. The cited literature is also appropriated and complete.

*However, some criticisms follows:*

1. My first concern regards your choice of representing the demonstrated movement as a sequence of postures and hence looking for synergies by using PCA or K-PCA analysis. Why not using functional PCA (f-PCA) analysis and determine the few moving synergies that make possible the execution of the demonstrated behaviours? It would be that, when you combine the local synergies in space and time by using functions  $\theta_k(q)$ , you get what you might obtain by using directly f-PCA. However, the last one are valid for the whole movement and can be combined by constant coefficients. [Honestly, I hadn't heard of functional-PCA until now. I searched a bit and I see why the reviewer would suggest this approach (which is interesting btw). F-PCA is the application of PCA on a functional space (mainly targeted at applications where each of the datapoints is a time-series). The goal is then to find the minimal set of eigen-time-series that best describes the shape of the observed time-series. To do this, each time-series is approximated with k basis functions and PCA is applied on these functions. The resulting eigen-functions are parametrized by a linear combination of these k basis-functions (looks very similar to k-pca/svc). First of all, I see a couple of complications: i) the basis functions are time dependent; i.e. they will only work for time-series of the same length as the datasets that they were learned from ii) the number of k basis functions is an open parameter, as well as the number of eigenfunctions to keep iii) I can understand how the reviewer would think that it is almost the same as finding the lower dimensional space via PCA/k-PCA and then fitting a GMM, as this would be equivalent to the 'k' basis functions. However, I'm not sure if the 'k' basis functions in joint space are equivalent to the 'K' clusters discovered by the GMM in the embedded space. Which is extremely important because this dictates how many A's we need. I might be wrong about these issues, I need to dig deeper into this.]
2. I also found the paper lacking of physical intuitions, especially in the experimental part, about the entities introduced in previous sections. In particular, what is the lesson we learn after your analysis of synergies and the obtained lower dimensional space for the few movements shown in section V? Is it possible to extract some global synergic behavior? Moreover, in section IV.A authors introduce the function  $\phi(q)$  named the embedding that maps the joint configuration into a lower dimensional space. Is it associated to a whole behaviour or, as matrices  $A_k$ , has a local validity? I lost this point. Can you show/report or describe what it represents in the joint space for one or more cases in Section V? What is this lower dimensional space for the cases in Section V? [Can be addressed through clarification and re-write]

3. A similar question for the matrices  $A_k$  that represent local, I would say postural (see previous comment), synergies whose dimension is  $m \times m$ , i.e. in joint space: I would expect they were defined in the lower dimensional space. [We actually address this in the discussion, it is related to the stability proof; i.e. we would lose rank when projecting the A matrix back to joint space] Moreover, are they local representation of the distribution of postures and hence covariance matrices? What do their eigenvectors and eigenvalues locally represent? Maybe, a comparison with the classical and more known postural synergies for the human hand, analyzed by PCA, could be useful. Finally, what does it mean that they should be positive definite (apart from stability issue)? [All of these questions can be addressed through clarification and re-write]
4. What is the dimension of function  $\theta_k(q)$  that, to some extent, can be seen as the new control variables. Is it  $K < m$ ? [Can be addressed through clarification and re-write]
5. For the test, why not comparing also with the JT control method? In other terms, is it possible to use a SEDS + JT, especially for the third case "Transiting through singular configurations"?
6. Minors: - SEDS + IK: what does SEDS mean? [We clearly say what it means on page 6: "For the Cartesian motion generator we use the SEDS approach [8] which learns an asymptotically stable DS in Cartesian space from demonstrations. We then generate joint trajectories through a damped least square IK solver. From herein we refer to this approach as SEDS+IK."]

Reviewer: 7 (Review30521)

The paper presents a kinematic controller for a robot, that drives it towards a fixed target in task space. The controller works in joint space and consists in a dynamical system formulated as a LPV system which combines different motor synergies. Such synergies are learnt from demonstrations. Theoretical proof of stability is given and experimental results are offered for validation.

The paper is very well written and nicely organized. Results are interesting and the technical accuracy of the paper is good. The coverage of the state of the art is quite good.

*I have the following comments:*

1. a considerable part of the introduction is spent in comparing joint space trajectory generation to task space trajectory generation. Since these are elementary concepts in robotics, the authors might consider reducing this part; [Can be addressed through clarification and re-write]
2. one of the main claims of the paper is the stability proof, which in fact is cited in the first line of the abstract. However the stability analysis is a quite simple extension of the stability of the transpose Jacobian scheme, where the constant gain on the task space error is replaced by the matrix  $A(q)$ . As such the emphasis on this result might be to some extent reduced. By the way, the proof works only if the Jacobian is full rank, which is not properly discussed in Appendix I; [Can (should) be addressed through clarification and re-write]
3. the meaning of variables  $\dot{q}_d$  in (2) is not very clear to me, as well as whether it takes the same meaning as  $\dot{q}_{t,n}$  in (8); [Can be addressed through clarification and re-write]
4. Section III uses the concept of synergy without actually defining it. An introduction to this concept is given later, in Section IV; [Can be addressed through clarification and re-write]
5. the expression "flow of motion" in Proposition 1 is not very clear to me; [Can be addressed through clarification and re-write]
6. some details about the optimization problem in (8) might be given (nature of the problem, complexity, feasibility). [Can be addressed through clarification and re-write]

