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Simple Synthetic Memories of Robotic Touch

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Abstract. It has been previously demonstrated in robots that the mimicking of functional characteristics of biologic memory can be beneficial for providing accurate learning and recognition in circumstances of social human-robot-interaction. The effective encoding of social and physical salient features has been demonstrated through the use of Bayesian Latent Variable Models as abstractions of memories (Simple Synthetic Memories). In this work, we explore the capabilities of formation and recall of tactile memories associated to the encoding of geometric and spatial qualities. Compression and pattern separation are evaluated against the use of raw data in a nearest neighbour regression model, obtaining a substantial improvement in accuracy for prediction of geometric properties of the stimulus. Additionally, pattern completion is assessed with the generation of 'imagined touch' streams of data showing similarities to real world tactile observations. The use of this model for tactile memories offers the potential for robustly perform sensorimotor tasks in which the sense of touch is involved.

Keywords: Tactile memories · Robot touch · Latent variable space · Tactile data generation.

1 Introduction

The emulation of the known functionality of biological memory systems represents an area of great potential towards the development of flexible and adaptive autonomous systems. Developing robotic systems able to effectively store memories from experiences contributes to the achievement of complex tasks through the use of contextual information on sensorimotor control. High-level abstractions of memory involve the reproduction of essential features such as compression of sensory data, pattern separation, and pattern completion [5]. These characteristics have inspired the development of computational memory models for spatial navigation [2] using Time Restricted Boltzmann Machines mimicking the structure and functionality of the Hippocampus; and in the context of social interaction with robots [11] characterising the aforementioned features trough Gaussian Process Latent Variable Models (GP-LVMs) [8] as the core for the development of Synthetic Autobiographical Memory Systems.

The formation and recall of memories in multiple sensory modalities have exploited the robustness of Bayesian Latent Variable Models [18], being able to produce meaningful representations of sensory data through non-linear dimensionality reduction and uncertainty quantification [4]. Prescott et al. [12] proposed the establishment of this family of models as Simple Synthetic Memories (SSMs). Active compression of high-dimensional data, creation of fantasy memories, and recovering of observations from latent spaces were explored for: face recognition, audition, action discrimination and tactile interactions. For the sense of touch, the data were obtained when the interacting human applied four different types of touch on the artificial skin of the robot. Results showed that the touch SSM was able to accurately recognise the type of tactile stimulus, therefore providing memory abstractions for passive tactile stimulation. Learned representations present the potential to be included in a closed loop for human-robot interaction, allowing speech and emotion-related facial expressions to be generated according to the context of the incoming tactile sensations.

The development of robotic systems able to interact with the environment requires the use of multiple sensing modalities. Incorporating the sense of touch to such systems has led to improvements in grasping, manipulation, and exploration of material and geometric properties. Tactile sensing involves the transduction of physical magnitudes akin to mechanoreception processes occurring in biological touch. The dimensionality of tactile data depends on the number of touch-sensitive elements contained in the sensing device. These tactile elements generally present a distribution within the artificial skin in a manner that the overlapping receptive fields deliver a highly correlated multidimensional signal in accordance to skin deformation. The formation of tactile memories can be related to the reduction of redundancies, and reveal invariances through compression of sensory signals.

It has been previously demonstrated that linear dimensionality reduction of systematically collected tactile data involving orientation and sensor position produces a structured manifold. The generated manifold reflects regularities from the observational space with the potential to support accurate perception of magnitudes for sensorimotor control [1]; specifically in the discrimination of angle and position of the sensor with respect to the edge of an object using non-parametric models in supervised learning [14]. Alternatively, non-linear dimensionality reduction has been studied in the context of learning a manifold to relate tactile data and actions for object recognition [17]. In addition, in [16] data efficiency in tactile exploration was addressed with online learning through the update of a GPLVM model with an intelligent policy for data collection by analysing similarities of incoming tactile data in the latent variable space.

Although non-linear dimensionality reduction for sensorimotor tasks has provided meaningful representations as an aid to perception, the use of GPLVMs as tactile memories with the capability to mimic the functionality of biological memories remains to be examined. In this work, we show that the formation of tactile memories previously demonstrated to provide accurate perception in a social interaction setting can be extended to the perception of magnitudes related to the execution of sensorimotor tasks. Specifically, we evaluate functional characteristics of memory such as compression, pattern separation, and pattern completion of tactile memories that encode geometric and spatial qualities. We show that improvements in accuracy of a nearest neighbour regressor can be achieved through the effective contextual separation capabilities of the SSM. Additionally, sensory observations related to 'imagined touch' are generated from the latent representations of test data. These generated tactile percepts appear to be noticeably similar to the real streams of data.

2 Methods

2.1 Robotic Setting

The systematic collection of tactile data containing implicit information regarding edge orientation and relative sensor position require a robotic platform able to perform movements with precision, and a tactile sensor mimicking the operation of mechanoreception. The robotic system (Fig. 1a), previously used for the execution of a tactile exploratory procedure [15], consists of a Cartesian robot with a soft biomimetic tactile sensor as the end effector.

Robotic Platform The formation of tactile memories that encode spatial quantities requires a robotic platform able to perform precise and accurate movements within the horizontal plane. The "Yamaha XYX" Cartesian robot produces highly accurate movements of approximately 20μm, thus being able to produce a consistent positioning of the sensor for the systematic collection of tactile data. The contact between the sensor and the surface of the object requires discrete vertical movements (taps onto the surface). This interaction with the object is performed with the action of an "Actuonix P-16" linear actuator. This device acts as a prismatic joint in a range of 50mm. The actuator does not produce precise and consistent vertical movements. However, the produced motion of the actuator allows the collection of tactile data in a less structured setting, being able to record signals more likely to occur in a real world setting.

Biomimetic Tactile Sensor Tactile data is acquired through the use of a TacTip sensor [3] mounted on the robotic platform. The TacTip is a soft biomimetic optical tactile sensor. The device consists of a 40mm-diameter compliant dome containing a distributed array of 127 markers inside the dome filled with a clear compliant acrylic polymer. A 3D printed structure is attached to the dome enclosing a webcam pointing towards the markers. The camera provides samples at 20 frames per second with a resolution of 640 x 480 pixels. The detection and tracking of the markers is achieved through computer vision techniques [9], delivering a continuous stream of data consisting of the horizontal and vertical positions of each of the markers. Therefore, delivering a 254-dimensional array per sample associated to the recorded position of each marker.

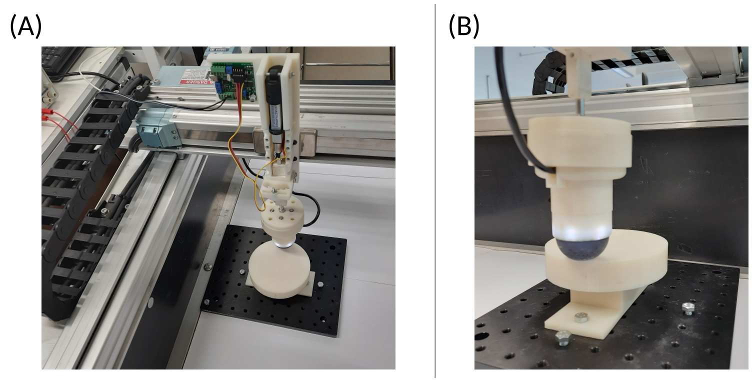

Fig. 1. Robotic setting. A) The Robotic platform consists of a Yamaha "XYX" robot and an Actuonix P-16 linear actuator vertical displacements. B) TacTip sensor [3] with the stimulus for data collection

2.2 Tactile Data Acquisition

The collection of data for the formation and recovery of tactile memories is systematically performed with the execution of discrete taps onto the periphery of the surface of an object. The object for tactile interaction is a 3D printed 2.5D flat surface with a circular shape, as depicted in Fig. 1b. The object was selected given that circular flat surfaces contain the majority of the possible relative edge orientations to be encoded in the latent space. Edge orientations are represented by the relative angle between the sensor and the edge of the object. Thus, for each relative orientation a set of taps are executed from a position of -9mm to 5mm in steps of 1mm where the 0mm position is located at the edge of the object.

The data acquisition procedure consists of aligning the centre of the compliant dome of the sensor to a distance of 9mm relative to the edge of the object. Consecutively, a vertical displacement of 4mm towards the surface is performed with a duration of 0.6 seconds. This time duration is taken into account from the beginning of the displacement until the fulfilment of the time. Thereafter, a vertical movement directed to the initial position is executed (Fig. 2a); at this stage, the data is recorded for 0.4 seconds. Subsequently, a pause of 1 second is set to make sure the shape of the compliant component of the sensor is restored. After a discrete tap is executed, the Cartesian robot performs a displacement of 1 mm in a direction towards the centre of the object following the radial axis of the constant movement angle relative to the orientation to be perceived (Fig. 2b). This procedure is repeated until the sensor reaches the final radial position (5 mm from the edge to the centre) for angles from 0 to 342 degrees in steps of 18 degrees. Therefore, obtaining 20 constant angle sets composed of taps from 17 equidistant positions; providing 340 discrete taps for training. Samples of the collected data can be observed in Fig. 2c, along with the distribution of the internal markers of the TacTip sensor (Fig. 2d)

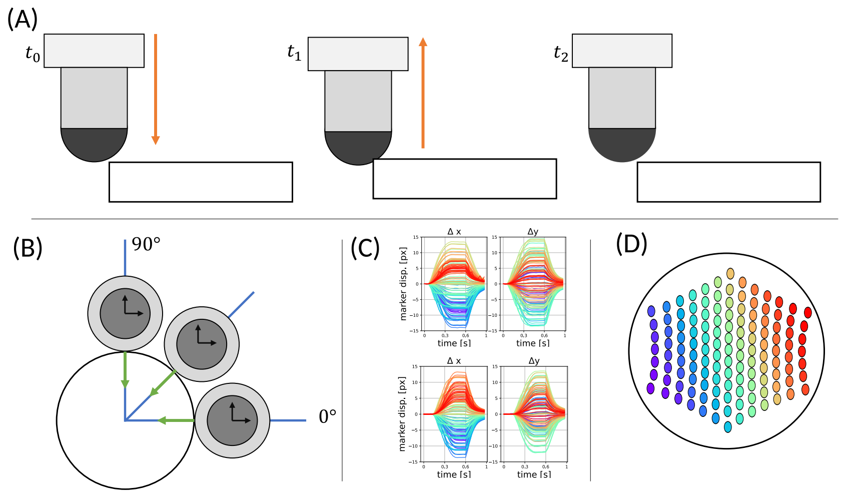

Fig. 2. Data collection procedure. A) Execution of a tap over the stimulus. B) Direction of sensor displacement for the collection of multiple taps for each edge orientation. C) Tactile data for taps located at 2mm from the edge to the centre for 0 and 90 degree orientations. D) Internal marker distribution of the sensor

2.3 Bayesian Latent Variable Model

The formation of tactile memories involves inferring latent representations from tactile sensory data and incorporating a generative component for recall and the generation of imagined touch. Gaussian Process Latent Variable models (GPLVMs) offer a powerful tool for nonlinear dimensionality reduction [8, 7]. These unsupervised learning models derive latent representations of the data through a generative mapping function, where observations (y) are related to latent variables (x) through the equation $y = f(x)+\epsilon$, with ϵ representing Gaussian noise. The Bayesian variant of the model (BGPLVMs) allows for further data compression through the use of inducing points to handle larger datasets [18]. Importantly, these low-dimensional latent variable descriptions of high-dimensional data exhibit properties akin to biological memory, including compression, pattern separation, and pattern completionn [4]. In our study, we employed the implementation of GPLVM from the GPy library [6] to train the Simple Synthetic Memory (SSM). The model utilized an RBF kernel with automatic relevance determination, as well as white noise and bias kernels. The latent representations were initialized through principal component analysis, and the positions of the latent points were optimized using the kernel hyperparameters.

The application of latent variable models, such as Gaussian Process Latent Variable models (GPLVMs), extends beyond theoretical considerations and finds practical utility in interactive scenarios. For instance, in the field of human-robot interaction, these models can enhance the robot's ability to perceive and interact with its environment. Consider a scenario where a robot is equipped with tactile sensors to explore and interact with objects. By employing GPLVMs, the robot can learn latent representations of tactile sensory data, enabling it to recognize and differentiate between various objects based on their tactile properties. This capability would allow the robot to adapt its grasping and manipulation strategies based on the inferred characteristics of the objects it encounters.

3 Results

3.1 Compression and Pattern Separation

With the systematically collected tactile dataset, the Latent Variable model were used to form tactile memories as latent representations of the data. The recognition of patterns from raw data, and the encoding of different contextual information are qualitatively demonstrated in the generated latent representation of the data, shown in Fig. 3. The tactile data was subject to a dimensionality reduction, generating a representation of the dataset in a three dimensional space, where each data-point is equivalent to the memory of a tap over the stimulus.

The encoded information within the manifold is related to the variables that were used to conduct the data acquisition. Fig. 3a, c. present the projection of the SSM on latent dimensions 0 and 1. The distribution of taps associated to different angles reveals a pattern separation over the latent dimension 1 (Fig. 3a). Similarly, as observed in Fig. 3c, the taps related to sensor position are distributed over the latent dimension 0. Pattern separation of tap representations is more evident on taps collected in positions from -9mm (labelled as class 0) to taps on the edge of the object, i.e. 0mm (labelled as class 10), denoting similarity between taps as the data is acquired towards the centre of the object. Additionally, Fig. 3b, d, can be seen as a illustration of the data collection process in which the different edge orientations are radially distributed (Fig. 3b), and where the positions of the sensor preserve the acquisition arrangement (Fig. 3d).

The quantification of pattern recognition and separation was performed through K-NN regressor models for raw data and compressed data. Taking into account the memory feature of encoding consistency, we used the same representations of memory to train and test a nearest neighbour regression model. The performance of the regression model, as a proxy for evaluating the compression and pattern separation of the SSM was quantified through the use of the R^2 score and the Mean Absolute Error (MAE) of test data predictions.

Table 1. Performance metrics for nearest neighbour regression model with data from the latent space

Metric	Angle	Position
R^2 (Raw)	0.824	0.983
R^2 (SSM)	0,992	0.985
M.A.E (Raw)	24.49[deg]	0.46[mm]
M.A.E (SSM)	2,54[deg]	0,34[mm]

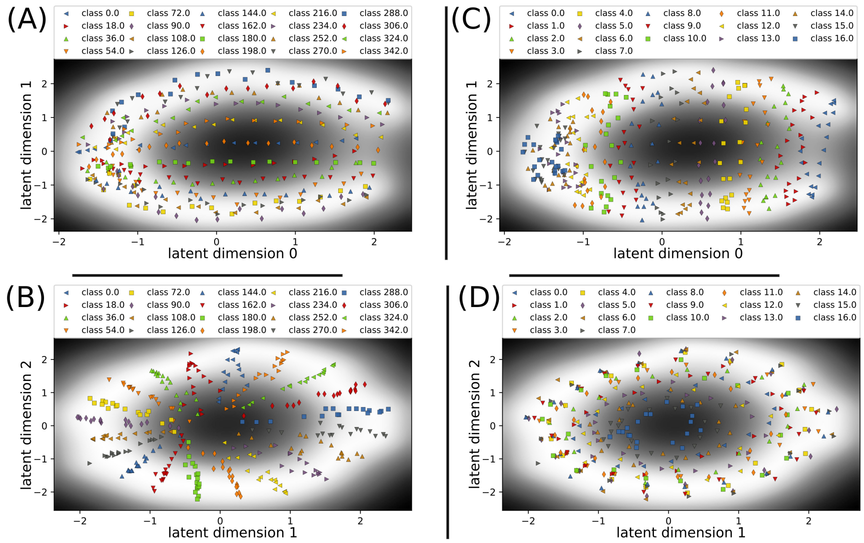

Fig. 3. Latent Representation of tactile memories. Compressed representation labelled as angle classes in the manifold, depicting latent dimensions: A) 0 and 1 B) 1 and 2. Representation labelled as position classes in the manifold, depicting latent dimensions: C) 0 and 1. D) 1 and 2. Each point is associated to a tap, the background intensities correspond to the uncertainty of predicting observations from latent variables

The coefficient of determination (R^2 score) provides insight into the goodness of fit of the model, thereby enabling an assessment of the model's ability to accurately predict unseen samples based on the extent of explained variance. The highest attainable score is 1. The R^2 score for angle and position indicate that a robust compression and pattern separation has been achieved. A high coefficient of determination can lead to accurate predictions, reflected in the obtained mean absolute error. Table 1 shows an increase in performance for the regression of both variables by effect of due to the pattern recognition property of the BGPLVM. Additionally, a relevant increase in performance for angle regression can be noticed. This improvement in accuracy reflects the pattern separation capabilities of the SSM.

3.2 Pattern Completion

The reconstruction of tactile observations from partial information was achieved through the generative mapping function of the Bayesian Latent Variable Model. In this work, taps from the test dataset were subject to dimensionality reduction trough the SSM. This compressed data was used to generate observation data, i.e. tactile data from the execution of a discrete tap. The produced data may be regarded as imagined touch given that no actions are required for its generation. The existence of differences between train and test observations were taken into account to quantify the correctness of the generated data. The mean of the point-to-point absolute distance between training and test data was calculated for each tap. A probability distribution was obtained to establish a baseline of the mean absolute distances that may be expected when comparing the real data with the generated data. In a similar manner, distributions for the differences between real and generated data were also obtained.

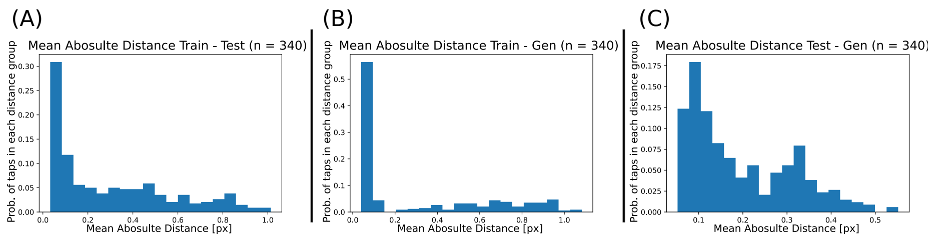

Fig. 4. Probability distributions for mean absolute distance: A)Train vs Test. B) Train vs Generated. C) Test vs Generated

Fig. 4 presents the probability distributions as representations of the mean distance between taps for: train and test data (Fig. 4a); train and generated data (Fig. 4b); test and generated data Fig. 4c. These metrics can be considered as a quantification of the error between observations. Differences between real and generated data should be expected due to the existence of differences from train and test real data. As expressed in Table 2, the minimum error for train vs test observational data denotes a difference of 0.007 pixels with respect to the train vs generated data. Samples of the minimum error obtained from the train vs gen. distribution (Fig. 4b) can be observed in Fig. 5; the similarity of the generated data with respect to the real data can be visually corroborated with a congruent displacement of the internal markers of the sensor. Similarly, the difference of 0.020 pixels corresponding to the minimum error from the test vs gen. distribution (Fig. 4c) substantiate the resemblance of the tactile observations presented in Fig. 6.

The observation data with the maximum error of train vs generated data (Fig. 7) provides a notion of the type of differences that might be expected. Although the majority of internal markers of generated data show a similar displacement compared to observations from the train dataset, some markers display differences in amplitude, specially following a displacement similar to the tap data of the test set. A similar effect can be noticed in the sample of maximum difference between test vs generated data (Fig. 8). However, in this case, the tap of the generated dateset appears to have more similarity to the observation from the train dataset than to the tap data from the test set.

A Mann-Whitney U test [10] was conducted to determine whether that samples from the obtained distributions come from the same population. The mean of absolute distances were assigned to three groups. Group 1: Train vs Test M.A.D;

Table 2. Maximum and minimum values for the mean of the absolute distances between real and generated observations

Metric	Train vs Test	Train vs Gen.	Test vs Gen.
Min. M.A.D.	0.032 [px]	0.039 [px]	0.052 [px]
Max. M.A.D.	1.013 [px]	1.082 [px]	0.551 [px]

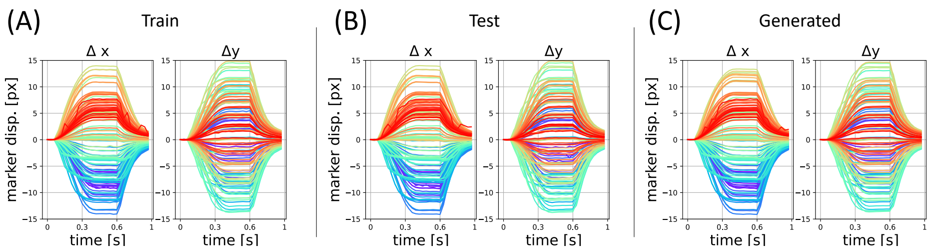

Fig. 5. Samples of tactile data for the minimum mean distance between train and generated data (0.039 pixels). Observation from: A) Train dataset, B) Test dataset, C) Generated dataset

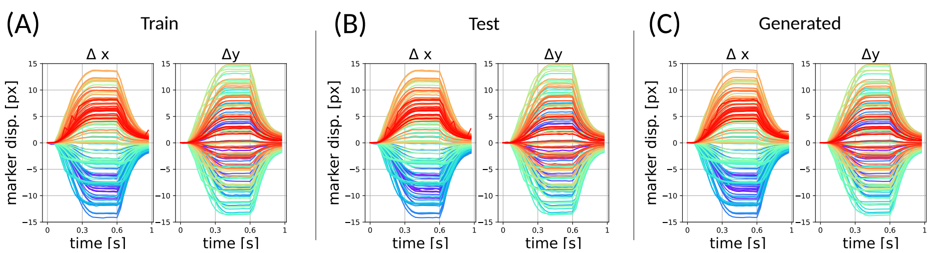

Fig. 6. Samples of tactile data for the minimum mean distance between test and generated data (0.052 pixels). Observation from: A) Train dataset, B) Test dataset, C) Generated dataset

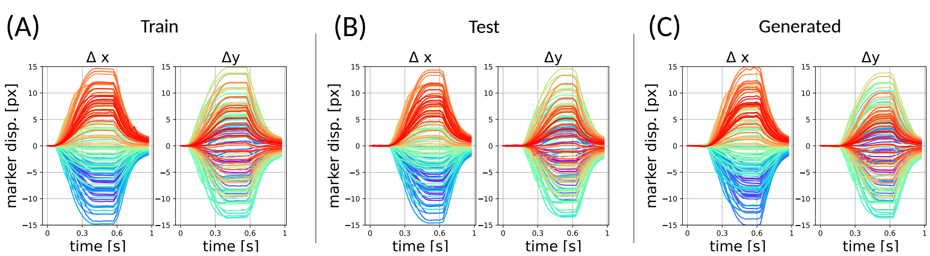

Fig. 7. Samples of tactile data for the maximum mean distance between train and generated data (1.082 pixels). Observation from: A) Train dataset, B) Test dataset, C) Generated dataset

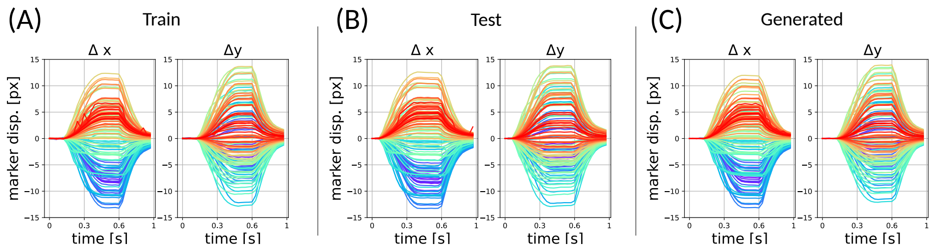

Fig. 8. Samples of tactile data for the maximum mean distance between test and generated data (0.551 pixels). Observation from: A) Train dataset, B) Test dataset, C) Generated dataset

Group 2: Train vs Gen. M.A.D; Group 3: Test vs Gen. M.A.D. A critical value of $\alpha = 0.01$ was set to avoid type I errors, i.e. obtaining false positives. With the null hypothesis that Group 1 and Group 2 come from the same distribution, a p-value of 0.093 was calculated. Similarly, with the null hypothesis of Group 1 and Group 3 coming from the same distribution, a p-value of 0.052 was obtained. For both cases there is weak evidence that the mean of the absolute distances do not come from the same population. Thus, failing to reject the null hypothesis. Qualitatively, these results are consistent with the similarity quantification as presented in Figs. 5- 8, where the generated tactile observations appear to be similar to the real streams of tactile data from the train and test datasets.

4 Discussion

Matching the functionality of biologic memory systems gives rise to the development of robust and adaptive perception in robots. As demonstrated in the context of social interaction, Latent Variable Models as Simple Synthetic Memories encode salient features of the physical and social world; thus, providing an efficient encoding of high-dimensional streams of data, and generative capabilities for the reconstruction of observation sensory data given a cue. These insights of memory formation and recall from social interaction were tested in the context of physical interaction, specifically in a setting of robotic tactile perception, where actions are required to be executed for the acquisition of tactile data. A systematically collected tactile dataset containing information regarding geometric and spatial quantities of a stimulus was used to train a Bayesian latent variable model. Simple synthetic memories for the encoding of streams of tactile sensory information provide meaningful representations in the produced latent variable space.

The organisation of the latent data-points according to sensor position and edge orientation provides evidence of pattern recognition and encoding of different contexts. In that sense, the improvement in the performance metrics of nearest neighbour regression using compressed data compared to raw data reveals the effects of pattern separation in the latent space. Recall and generation of tactile memories was attained through the generative capabilities of the SSM. The similarity of the observations between the generated dataset with respect to the train and test dataset was evaluated by calculating a metric related to the error between real and generated data. As errors between train and test data appear to be present due to the response of the linear actuator that executes vertical movements in data acquisition, we could determine that the errors of train and test touch vs imagined touch followed similar probability distributions. This outcome was confirmed with the application of a Mann-Whitney U test, determining that distributions of train-gen. error and test-gen. error might come from the same population. Additionally, the similarity between real and generated data was depicted by showing the samples in which the minimum and maximum error was obtained (Figs. 5- 8), demonstrating a similar and congruent pattern of displacement of the internal markers of the sensor.

The use of Simple Synthetic Memories of touch may be considered as an abstraction of the posterior parietal cortex of non human primates where convergence of cutaneous and proprioceptive inputs appear to take place [13]. In robotic systems, the encoding of spatial and geometric qualities from tactile data can support the completion of complex sensorimotor tasks by providing robust representations of memories and generating 'imagined touch' streams of data for planning optimal movements in the execution of tasks such as grasping, manipulation and tactile property exploration.

To provide a practical example, let's consider the potential application of SSMs in tactile perception for robots. By encoding memories within the tactile sensory modality, SSMs can enable robots to efficiently capture and process tactile information. Imagine a robot equipped with tactile sensors on its fingertips, which can detect and gather rich tactile data from interactions with objects or surfaces. To make sense of this data and generate meaningful representations, the robot can employ SSMs, utilizing Gaussian Process Latent Variable models (GPLVMs) to derive low-dimensional latent representations of the tactile data.

These SSMs trained on tactile data could enable the robot to perform various tasks related to tactile perception. For example, the robot could learn to recognize different textures by encoding tactile memories of various surfaces. When presented with a new tactile stimulus, the robot could use pattern completion techniques to reconstruct the complete texture based on a partial cue. This ability would be particularly useful when exploring unfamiliar objects or environments. Furthermore, SSMs can facilitate pattern separation, enabling the robot to distinguish between different tactile patterns. This would allow the robot to recall distinct patterns of interaction, even if they share some similarities in terms of tactile properties. By leveraging the memory capabilities of SSMs, the robot could navigate its environment, manipulate objects, and interact with humans using tactile information in a more human-like and context-aware manner.

While the practical example described above demonstrates the potential of SSMs in tactile perception for robots, further research and development are needed to realize this application fully. Future works could focus on training SSMs specifically for tactile data, exploring different strategies for encoding and processing tactile information, and evaluating the performance of SSM-based tactile perception systems in real-world robotic scenarios. By incorporating SSMs into tactile perception, robots could enhance their ability to interact with the physical world and engage in tasks that require tactile sensitivity opening new possibilities for robotic applications.

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Competing interests

TJP is a director and shareholder in two robotics companies—Consequential Robotics Ltd and Bettering Our Worlds (BOW) Ltd. These companies are not expected to benefit from this publication. PJS has no competing interests.

References

1. Aquilina, K., Barton, D.A., Lepora, N.F.: Principal components of touch. In: Proceedings - IEEE International Conference on Robotics and Automation. pp. 4071–4078. Institute of Electrical and Electronics Engineers Inc. (9 2018). https://doi.org/10.1109/ICRA.2018.8461045
2. Boorman, L.W., Damianou, A.C., Martinez-Hernandez, U., Prescott, T.J.: Extending a hippocampal model for navigation around a maze generated from real-world data. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). vol. 9222, pp. 441–452. Springer Verlag (2015). https://doi.org/10.1007/978-3-319-22979-9_44
3. Chorley, C., Melhuish, C., Pipe, T., Rossiter, J.: Development of a tactile sensor based on biologically inspired edge encoding. In: 2009 International Conference on Advanced Robotics, ICAR 2009 (2009)
4. Damianou, A., Ek, C.H., Boorman, L., Lawrence, N.D., Prescott, T.J.: A top-down approach for a synthetic autobiographical memory system. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). vol. 9222, pp. 280–292. Springer International Publishing (2015). https://doi.org/10.1007/978-3-319-22979-9_28
5. Evans, M.H., Fox, C.W., Prescott, T.J.: Machines learning - Towards a new synthetic autobiographical memory. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). vol. 8608 LNAI, pp. 84–96. Springer Verlag (2014). https://doi.org/10.1007/978-3-319-09435-9_8
6. GPy: {GPy}: A Gaussian process framework in python. \url{http://github.com/SheffieldML/GPy} (2014)
7. Lawrence, N.: Probabilistic non-linear principal component analysis with Gaussian process latent variable models. Journal of Machine Learning Research **6**, 1783–1816 (2005)

8. Lawrence, N.D.: Gaussian process latent variable models for visualisation of high dimensional data. In: Advances in Neural Information Processing Systems (2004)
9. Lepora, N.F., Aquilina, K., Cramphorn, L.: Exploratory Tactile Servoing With Active Touch. IEEE Robotics and Automation Letters **2**(2), 1156–1163 (4 2017). https://doi.org/10.1109/LRA.2017.2662071
10. Mann, H.B., Whitney, D.R.: On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. The Annals of Mathematical Statistics **18**(1), 50–60 (4 1947), http://www.jstor.org/stable/2236101
11. Martinez-Hernandez, U., Damianou, A., Camilleri, D., Boorman, L.W., Lawrence, N., Prescott, T.J.: An integrated probabilistic framework for robot perception, learning and memory. In: 2016 IEEE International Conference on Robotics and Biomimetics, ROBIO 2016. pp. 1796–1801 (2016). https://doi.org/10.1109/ROBIO.2016.7866589
12. Prescott, T.J., Camilleri, D., Martinez-Hernandez, U., Damianou, A., Lawrence, N.D.: Memory and mental time travel in humans and social robots. Philosophical Transactions of the Royal Society B: Biological Sciences **374**(1771), 20180025 (4 2019). https://doi.org/10.1098/rstb.2018.0025
13. Sakata, H., Shibutani, H., Kawano, K.: NEURAL CORRELATES OF SPACE PERCEPTION IN THE PARIETAL ASSOCIATION CORTEX OF THE MONKEY. In: Brain and Behaviour, pp. 291–298. Pergamon (1 1981). https://doi.org/10.1016/b978-0-08-027338-9.50047-5
14. Salazar, P.J., Prescott, T.J.: Deep Gaussian Processes for Angle and Position Discrimination in Active Touch Sensing. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). vol. 13499 LNAI, pp. 41–51. Springer Science and Business Media Deutschland GmbH (2022). https://doi.org/10.1007/978-3-031-16770-6_4
15. Salazar, P.J., Prescott, T.J.: Tactile and Proprioceptive Online Learning in Robotic Contour Following. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). vol. 13546 LNAI, pp. 166–178. Springer Science and Business Media Deutschland GmbH (2022). https://doi.org/10.1007/978-3-031-15908-4_14
16. Stone, E.A., Lepora, N.F., Barton, D.A.: Learning to live life on the edge: Online learning for data-efficient tactile contour following. In: IEEE International Conference on Intelligent Robots and Systems. pp. 9854–9860. Institute of Electrical and Electronics Engineers Inc. (9 2020). https://doi.org/10.1109/IROS45743.2020.9341565, http://arxiv.org/abs/1909.05808
17. Tanaka, D., Matsubara, T., Ichien, K., Sugimoto, K.: Object manifold learning with action features for active tactile object recognition. In: IEEE International Conference on Intelligent Robots and Systems. pp. 608–614. IEEE (9 2014). https://doi.org/10.1109/IROS.2014.6942622
18. Titsias, M.K., Lawrence, N.D.: Bayesian Gaussian process latent variable model. In: Journal of Machine Learning Research. vol. 9, pp. 844–851. JMLR Workshop and Conference Proceedings (3 2010)