A Self-learning and Adaptive Control Scheme for Phantom Prosthesis Control Using Combined Neuromuscular and Brain-Wave Bio-Signals

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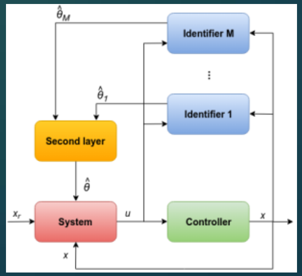


Contents

Overview and Problem Statement

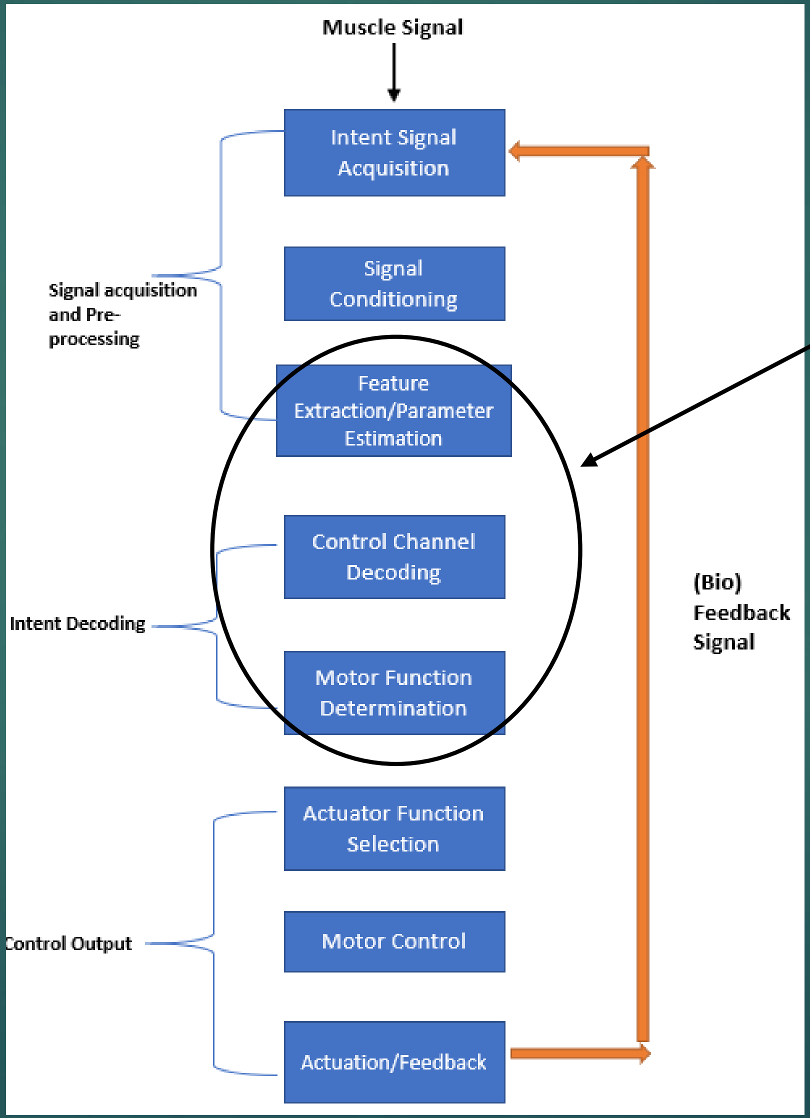
- **Estimated** to be around **6,000 amputations** (National Amputee Statistical Database (NASDAB))



- Although Upper Limb amputees make up **small segment** of amputees - they have **high functional needs**
- With **Trauma** reported as main **cause** of amputation
- **Loss** of upper limb is said to influence overall **independence** & **ability to work**

Overview and Problem Statement

Functional Prosthesis/Myoelectric Prosthesis Control Scheme



Pattern Recognition/Motion Intent Decoding Sequence

Overview and Problem Statement

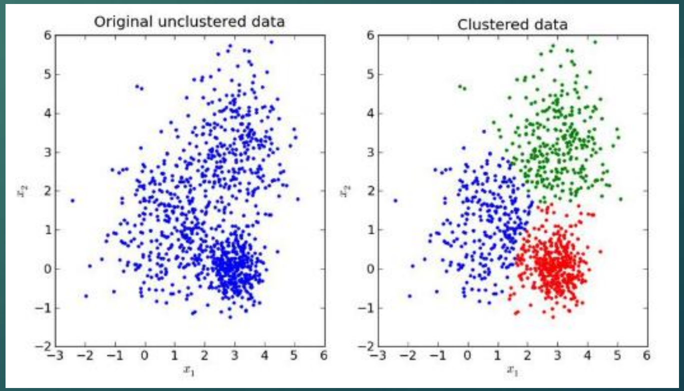
- Current Limitations of Pattern Recognition Control:

- Intent decoders/Classifiers are trained via the 'Supervised Learning' framework - thus, expert in loop required & lag time induced from training process

- Classifier degradation due to uncertainties i.e. electrode shift, physiological changes in stump etc

- Proposed Solution

- Design of Self Learning and Adaptive Controllers with 'Unsupervised Learning' framework which can help further enhance intuitiveness of prosthesis control and increase overall autonomy



https://medium.com/the-21st-century/machine-learning-a-strategy-to-learn-and-understand-chapter-3-9daaad4afc55

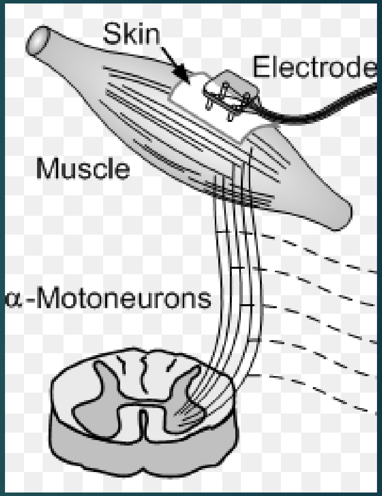
Biosensors and Data Collection

- ## Electromyography (EMG)

Represent superimposed electrical manifestations of action potentials from motor neurons, and can be mathematically modelled using dipole theory as a continuous extracellular action potential from a multiple source as seen in equation 1:

$$\phi_e(t) = -\frac{a^2.\sigma_i}{4.\sigma_e}.\int_{-\infty}^{+\infty}\frac{\partial IAP(x,t)}{\partial x}.a_x^-.\frac{\partial}{\partial x}\left(\frac{1}{r(x)}\right)dx \qquad (1)$$

Where $\boldsymbol{\phi_e}$ is the time varying extracellular potential, $\boldsymbol{\sigma_e}$ is the conductivity of the extracellular medium, $\boldsymbol{\sigma_i}$ is the intracellular conductivity, $\boldsymbol{a}$ is the radius of the fiber, $\boldsymbol{t}$ is time, $\boldsymbol{r}$ is the distance of the source excitation to the recording sensor, $\boldsymbol{x}$ is a point in space within the fiber element, $\boldsymbol{a_x^-}$ is the length of the anatomical fiber and $\boldsymbol{\frac{\partial IAP}{\partial x}}$ is the dipole strength at a point along the fiber axis.



http://www.bu.edu/ids/research-projects/muscles-alive/

- ## EMG Sensors

The EMG instrumentation used for data acquisition by Li et al [1] was the Refa 128 high-density electrodes by TMS International BV, Netherlands, with 32 electrodes [2]. The acquisition electronics comprised of a bandpass filter in the 10-500Hz frequency range, 24bit resolution and a sample rate of 1024Hz.

1. Li, X.; Samuel, O.W.; Zhang, X.; Wang, H.; Fang, P.; Li, G. A motion-classification strategy based on sEMG-EEG signal combination for upper-limb amputees. *J. NeuroEng. Rehabil.* **2017**, *14(2)*, doi: 10.1186/s12984-016-0212-z
2. Nsugbe E.; Phillips C.; Fraser M.; McIntosh, J. Gesture Recognition for Trans-humeral Prosthesis Control Using EMG and NIR. *IET Cyber-Systems and Robotics* **2020**, doi: 10.1049/iet-csr.2020.0008

Biosensors and Data Collection

Electroencephalography (EEG)

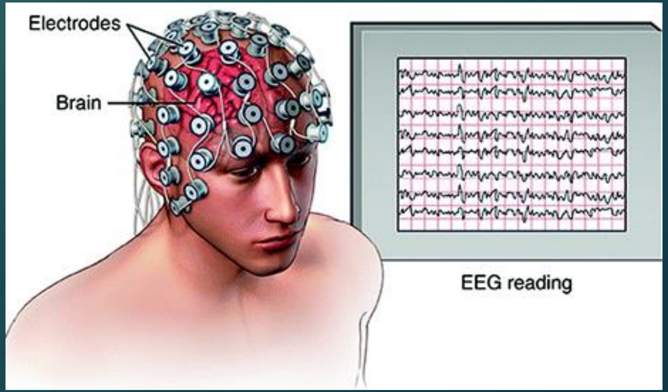
EEG signals occur from the synchronous neuronal firing of billions of pyramid-like cells within the skull of a human being. Using a combination of dipole theory, and assuming the forward EEG problem, a measured potential of an EEG signal can be formulated as follows :

$$u(r_s, q, x) = \frac{||q||}{4\pi\sigma_L r_L^2} = \sum_{n=1}^{\infty} \frac{2n+1}{n} \left(\frac{r_s}{r_L}\right)^{n-1} f_n[ncos \propto P_n(cos\gamma) + cos\beta sin \propto P_n^1(cos\gamma)] \qquad (2)$$

Where s is the dipole source located within proximity of sphere of radius r_s of moment q, boundary sphere r_L, σ_L anisotropic conductivity within boundary sub-domain of L, f_n is the EEG measurement for nth element in the infinite set, $\propto$ is the angle between the point S and measurement point x, γ is the angle between two planar vectors pairs of S & q and S & x, P_n and P_n^1 represent the Legendre polynomial coefficient of the series.

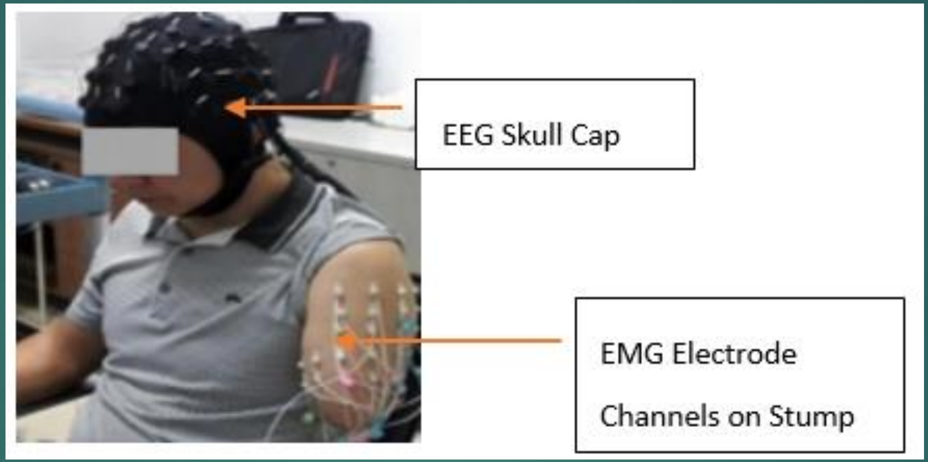
EEG Sensors

The 64 sensors EEG channel EasyCap, Herrsching, Germany, with the Al-AgCl electrodes and Neuroscan system version 4.3 was used. The EEG signals were band passed filters in the region of 0.05-100Hz with a sample rate of 1024Hz.



Data Collection

- Simultaneous acquisition of EMG and EEG signals



- The Hand Open and Hand Close Gestures were used for the work done as part of this paper and represent key hand gestures in prosthesis control

Proposed Self-Learning Architecture

- Assuming the acquisition of a bio-signal, the Self-Learning architecture comprising of an electrode selection process followed by a 3-phase self learning process as seen below:

0.1 *Optimal Electrode Channel Selection*

1. Feature Extraction and Fusion

2. Dimensionality Reduction

3. Iterative Clustering

Proposed Self-Learning Architecture

0.1 Optimal Electrode Channel Selection

- A first stage dimensionality reduction process which was done using a greedy search algorithm termed **Sequential Forward Selection** (SFS)

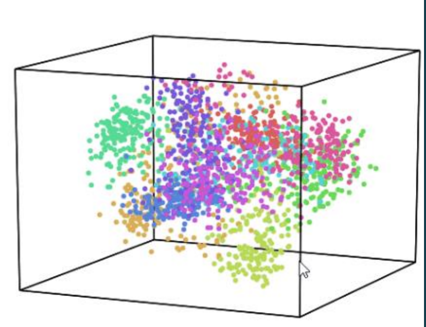
Create an empty set: $Y_k = \{\emptyset\},\ k = 0.$
Select best remaining feature:
$x^+ = arg\ max_{x^+ \in Y_k} [J(Y_k + x^+)]$
If $J((Y_k + x^+) > J((Y_k)$

a. Update$Y_{k+1} = Y_k + x^+$
b. $k = k + 1$
c. Go back to step 2.

- From which 10 optimal Electrodes were selected for both EMG(from 32) and EEG(from 64)

Proposed Self-Learning Architecture

1. Automated Feature Extraction and Vector Fusion



EMG Bio-signal

EMG Bio-signal

Mean Absolute Value- $\frac{1}{N}\sum_{n=1}^{N}|x_n|$

Waveform Length- $\sum_{n=2}^{N}|x_n - x_{n-1}|$

Zero Crossing- $\sum_{n=1}^{N} sgn(-x_i x_{i+1})\ \ Sgn(x) = \begin{cases} 1, & x > 0 \\ 0, & otherwise \end{cases}$

No. of Slope Sign Changes- $\sum_{n=1}^{N} sgn(-x_i x_{i+1})\ \ Sgn(x) = \begin{cases} 1, & x > 0 \\ 0, & otherwise \end{cases}$

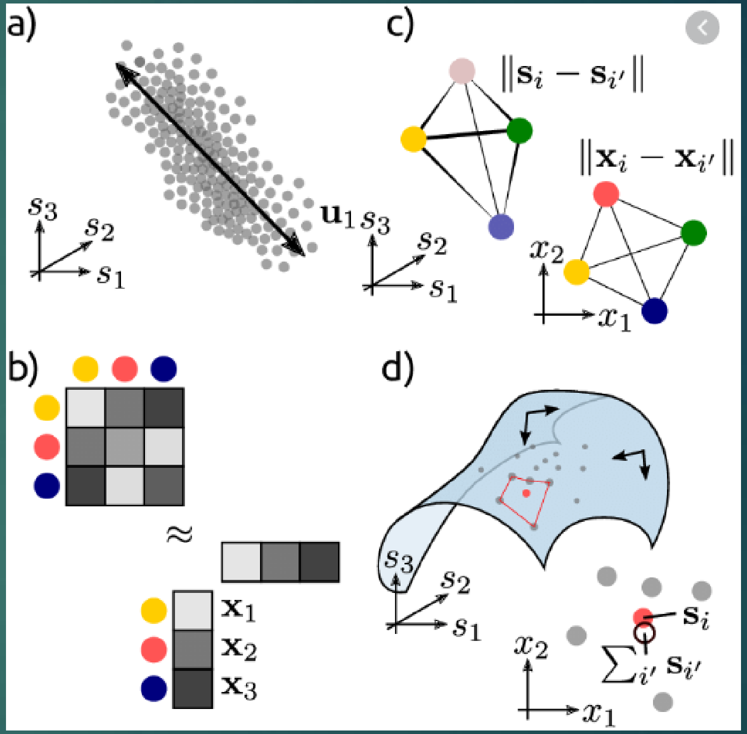
EMG Features	EEG Features

Proposed Self-Learning Architecture

2. Dimensionality Reduction

Dimensionality Reduction with Principal Component Analysis (PCA)
Associated Steps:
- **Mean Centring and Covariance Calculation**
- **Eigenvalues & Eigenvectors calculation, sorting and truncation**

First 2 PC's were selected which accounted for 95% of the info in the data



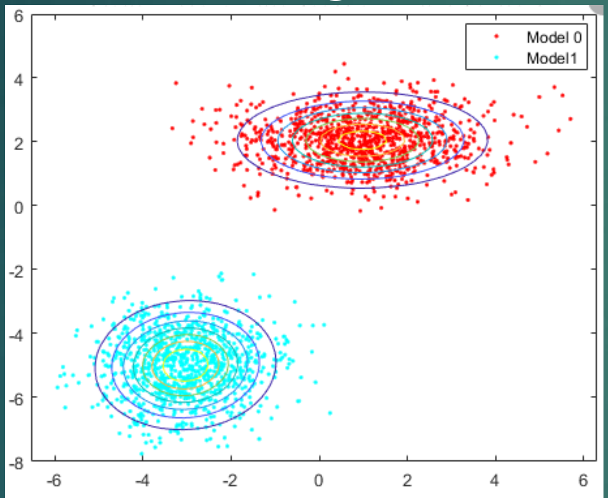
https://www.researchgate.net/publication/332536913_Unsupervised_machine_learning_in_atomistic_simulations_between_predictions_and_understanding

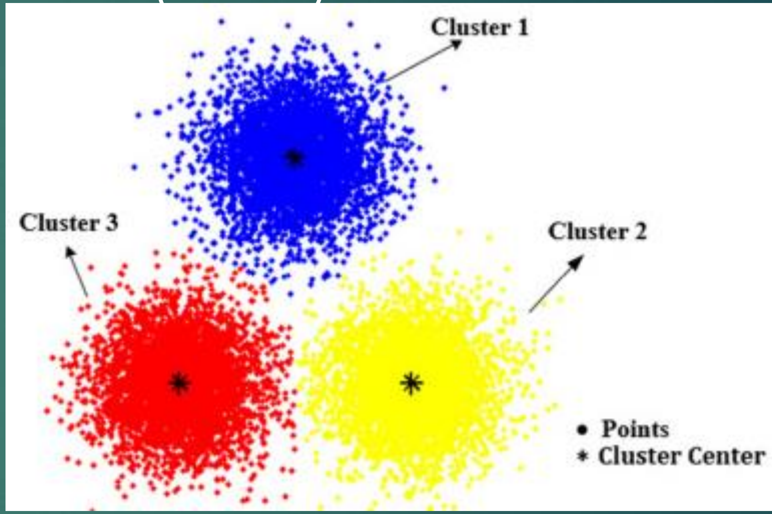
Proposed Self-Learning Architecture

3. Iterative Clustering

- Comparison Case Study involved two Unsupervised learning methods; K-Means clustering and Gaussian Mixture Model(GMM)

GMM





K-Means

No. of clusters = No. of hand gestures

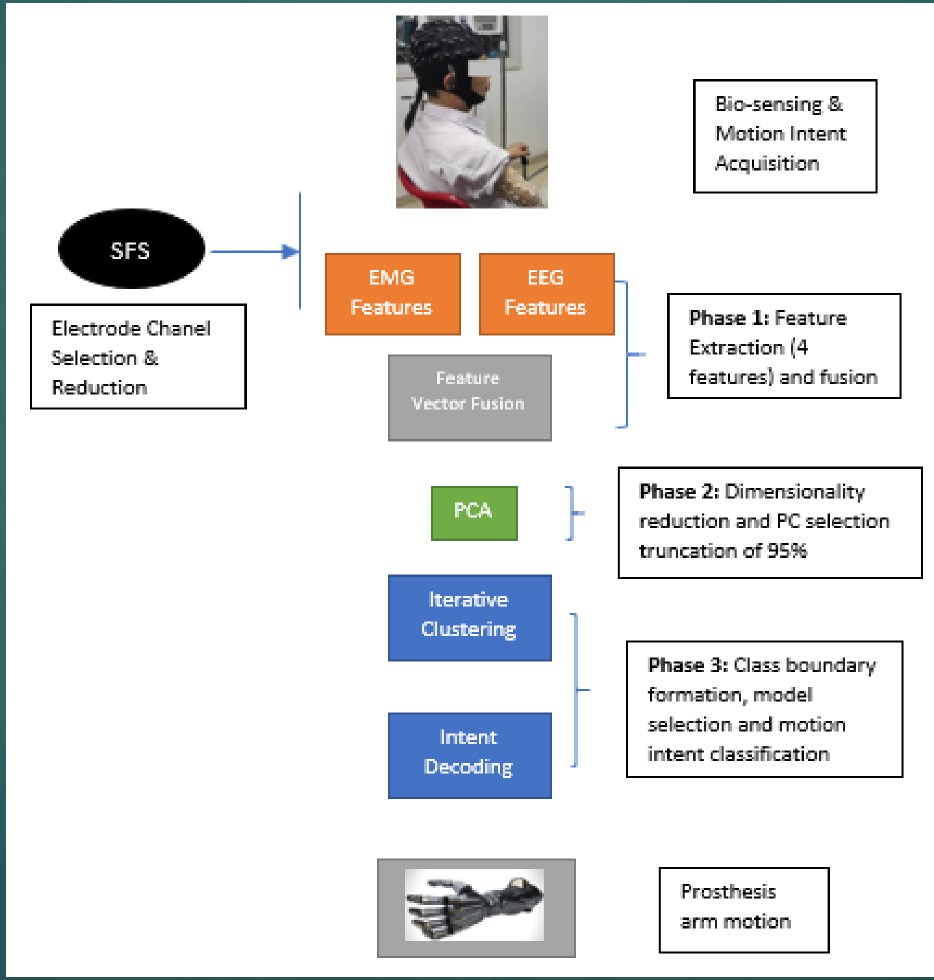
Cluster assignment was run 5 times each with the model that produced lowest performance index *J* selected

$$J = |(Number\ of\ motion\ repetitions\ performed * Number\ of\ electrode\ channels) - \sum_{i=1}^{m} x_k^i|$$

Where x_k^i is a data point assigned to a specific class k

Proposed Self-Learning Architecture

- Flow diagram of Self-Learning process



Results

- For different sensor configurations i.e. EMG only, EEG only and EMG-EEG

	GMM-EMG Only	K-Means-EMG Only	GMM-EEG Only	K-Means-EEG Only	GMM-EMG-EEG	K-Means-EMG-EEG
Cluster Model 1 Accuracy	83%	81%	64%	63%	68%	83%
Cluster Model 2 Accuracy	99%	81%	64%	58%	98%	83%
Cluster Model 3 Accuracy	99%	81%	64%	58%	98%	83%
Cluster Model 4 Accuracy	99%	81%	64%	58%	98%	83%
Clustering Model 5 Accuracy	99%	81%	64%	58%	70%	83%
Hold-Out Test Accuracy	100%	80%	90%	60%	100%	80%

Selected Model from each iteration highlighted in red

Possible Extension towards Adaptive Control

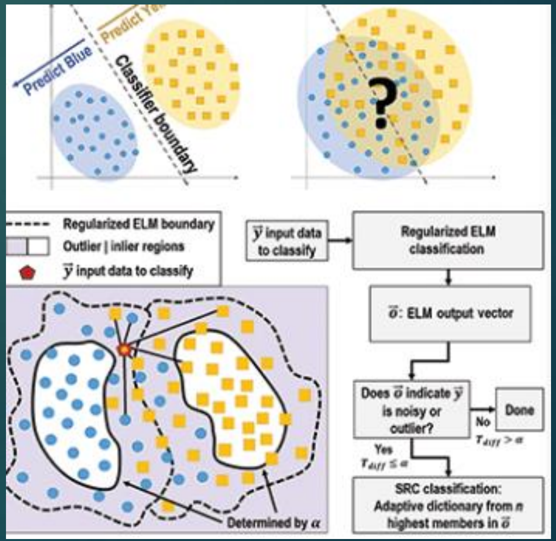
- *Extension of Self Learning Control towards Adaptive Control*

- Classifier Re-calibration to adapt to dynamic changes in the signal acquisition chain, which ultimately causes classifier degradation i.e. electrode shifts and physiological changes in stump

- The Self-learning process for classifier recalibration - thus a form of Adaptive Control, can be initiated in either of two ways:

**As an interrupt following a series of misclassified motion intents*

**As an interval based re-calibration prompt*



https://www.embs.org/tbme/articles/limb-position-tolerant-pattern-recognition-myoelectric-prosthesis-control-adaptive-sparse-representations-extreme-learning/

Conclusion and Further Work

Conclusion

- A 3-phase Self Learning Controller framework has been proposed to help reduce lag-time in the prosthesis controller customization

- The Self Learning Control scheme consists of Feature Extraction Stage, Dimensionality Reduction and Unsupervised Iterative Clustering

- The control architecture can also be extended towards an adaptive framework to minimize classifier degradation due to drifts and uncertainties

Further Work

- Validation of designed control architecture on a wider cohort of Transhumeral amputees

- Further formalisation of the prospect of the adaptive control framework

Acknowledgements

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