Neural decoding of Dreams

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Introduction

According to van Gerven, Seeliger, Güçlü, & Güçlütürk (2019), " neural decoding refers to the extraction of semantically meaningful information from brain activity patterns". This method provides a framework for addressing a fundamental question in neuroscience: how does the brain encode sensory and motor experiences through its activity? Neural decoding interprets which properties of stimuli are encoded in specific brain regions, offering insights into cognitive processes such as imagery, memory, and dreaming (van Gerven et al., 2019 p. 379).

Machine learning is a common approach for creating "neural decoders". These algorithms are trained to predict stimuli from previously observed brain activity for different stimuli (van Gerven et al., 2019). The methods have demonstrated various levels of statistically significant success in decoding multiple modalities in multiple contexts. Horikawa et al. (2013) decoded visual stimuli in dreams. In non-sleep-related areas, Bellier et al. (2023) reconstructed music from brain activity, and Güçlütürk et al. (2017) reconstructed pictures of observed faces.

This paper focuses on the application of neural decoding to dream research. By examining current methodologies and identifying limitations, this paper explores the future potential of decoding abstract and multimodal experiences during sleep.

Neural decoding of Dreams

Research on the neural decoding of dreams is an emerging field, with a limited number of laboratories actively contributing to this area. Notably, the Kamitani Laboratory at Kyoto University has made significant strides in decoding visual imagery during sleep (Horikawa et al., 2013). Most published studies have concentrated on reconstructing visual aspects of dream content. For example, Horikawa and Kamitani demonstrated the ability to predict dreamed objects from brain activity during sleep (Horikawa & Kamitani, 2016). However, a comprehensive decoder capable of simultaneously reconstructing multiple facets of dream content—such as imagery; auditory, olfactory, and gustatory experiences; and motor activities—has yet to be developed. Current methodologies focus primarily on visual elements, leaving other sensory and cognitive aspects less explored. In this section, we analyze the progress in decoding visual stimuli from dreams and discuss the potential for integrating other sensory modalities into future dream decoding research.

Decoding Visual Stimuli in Dreams

Horikawa et al. (2013) explored how the brain represents visual content during dreams, using machine-learning models to decode neural activity. The authors focused on the hypnagogic phase, the transitional period between wakefulness and sleep, where dreaming often occurs. The participants were frequently awakened during this phase to report their visual experiences, which were then mapped onto a lexical database of visual concepts. Functional magnetic resonance imaging (fMRI) data collected immediately before awakening were used to identify patterns of brain activity associated with specific visual imagery.

Horikawa et al. (2013) hypothesized that the visual cortical activity associated with perception while awake might share patterns with visual imagery during sleep. To test this, they trained decoding models on brain activity induced by viewing real images. These models were then applied to brain activity recorded during sleep, with the aim of classifying and identifying dream content.

The study demonstrated that decoding visual content during dreams via brain activity patterns is feasible, achieving an average accuracy of 60% for distinguishing between two visual categories, significantly exceeding the chance level of 50%. For pairs of visual categories that were more distinct, the accuracy improved to approximately 70%. High-level visual cortical regions, such as the lateral occipital complex and fusiform face area, showed better decoding performance than lower-level areas, such as the primary visual cortex, which is consistent with their role in processing complex, object-level features. When multiple visual elements were examined simultaneously, decoding performance varied across categories, with some exceeding chance levels. Importantly, the study highlighted a strong overlap in brain activity patterns between wakeful perception and dream imagery, reinforcing the hypothesis that shared neural mechanisms underlie both experiences (Horikawa et al., 2013).

In a follow-up study, Horikawa & Kamitani (2016) extended this work by incorporating features derived from deep neural networks (DNNs) to investigate hierarchical visual representations in the brain. Using decoders trained on DNN-derived features from perception experiments, the authors tested their ability to decode visual features of dreamed objects. They reported significant positive correlations between decoded features and actual object features in higher visual areas, particularly at mid- to high-level DNN layers. They also showed that dreamed object categories could be identified at above-chance levels, with certain brain regions (such as the lateral occipital complex and fusiform face area) outperforming others. This study demonstrated that dreams recruit hierarchical visual representations similar to those involved in perception (Horikawa & Kamitani, 2016).

Extending neural decoding to other modalities of dreaming

While visual stimuli in dreams can be decoded above chance levels, the decoding of other modalities, such as motor, auditory, olfactory, and gustatory experiences, remains underexplored. However, advancements in related areas suggest potential pathways for future research.

Dresler et al. (2011) investigated the activation of the sensorimotor cortex during dreamed movements in lucid dreaming participants. By comparing brain activity during dreamed hand clenching, imagined hand clenching, and actual hand clenching, researchers have identified significant overlap in activation patterns. Notably, activation was strongest during actual movements, followed by dreamed and imagined movements. This study highlights the potential for decoding motor-related dream activity, but the reliance on lucid dreaming participants raises questions about whether such findings can be generalized to nonlucid dreamers. Future studies should use nonlucid dreaming participants and detailed dream reports to validate these findings.

In nondream contexts, researchers have successfully decoded motor activities with varying degrees of accuracy. For example, upper-limb movements such as hand grasping and elbow flexion were decoded with 66% accuracy (Sugata et al., 2012), whereas directional reaching (up, down, left, right) was decoded at 39.5% accuracy, significantly above the 20% chance level (Shiman et al., 2015). Finer movements, including single-finger flexion, single-finger extension and two-finger combinations, achieved accuracies as high as 99% when activation patterns of approximately 30 neurons were used (Shin et al., 2009). While these studies do not directly address dream decoding, the strong correlations between awake and dreamed motor activity, as demonstrated by Dresler et al. (2011), suggest that similar methods could be applied to dream decoding.

The extension of decoding techniques to auditory, olfactory, and gustatory modalities presents additional challenges. King (2006) demonstrated that auditory imagery, such as imagining or anticipating sounds, elicits neural activity patterns in the auditory cortex similar to those evoked by actual auditory stimuli. Moses et al. (2019) decoded spoken and heard speech components in real-time, whereas Bellier et al. (2023) reconstructed music via nonlinear decoding algorithms.

Although these studies provide valuable insights, the lack of direct evidence linking brain activity during dreamed auditory experiences to waking experiences limits their applicability to dream decoding. Future research should prioritize identifying overlaps between real and dreamed auditory stimuli to establish a foundation for decoding dreamed auditory content.

Olfactory and gustatory modalities are even less explored in the context of neural decoding. Bensafi et al. (2003) reported that imagining odors activates neural substrates in the piriform cortex, similar to actual olfactory perception. However, there is no evidence yet connecting such activation patterns to dreamed olfactory experiences. Similarly, research on decoding gustatory perception remains sparse, with little to no exploration of its potential application to dreams. Given that visual and auditory experiences dominate dream content (Zadra et al., 1998), the limited focus on olfactory and gustatory decoding is perhaps unsurprising. Nevertheless, expanding decoding efforts to these modalities could enhance our understanding of the multisensory nature of dreaming.

Future Research

Future research should prioritize exploring the overlaps between brain activity evoked by dreamed and experienced auditory, olfactory, and gustatory stimuli. The limited focus on these sensory modalities has restricted our understanding of the multisensory nature of dreams. Expanding decoding research on olfactory and gustatory perceptions is crucial to gaining a more comprehensive understanding of how these experiences are represented in the brain.

In addition to sensory modalities, comprehensive dream decoding should emphasize more abstract experiences, such as inner speech, thoughts, and emotions. For example, Liwicki et al. (2022) successfully decoded 5 vowels and 6 words from inner speech with 35.20% and 29.21% accuracy, respectively. Kim et al. (2023) demonstrated the ability to decode thoughts along dimensions such as self-relevance and emotional valence. Among these abstractions, decoding the emotional content of dreams appears to be more advanced. Scarpelli et al. (2019) argued that similar neural substrates are involved in both dreaming and wakeful emotional regulation, suggesting that emotion decoding in dreams may benefit from existing research on wakeful emotional processing. Similarly, Lu et al. (2020) identified positive and negative emotions in awake subjects with 85.11% accuracy via EEG signals, highlighting the feasibility of emotion decoding in dream states.

Conclusion

In this paper, we introduced the concept of neural decoding and explored its application in the context of dreams. We reviewed the progress in decoding various modalities of dreams, highlighting both achievements and current limitations. Furthermore, we identified future directions for research, emphasizing the potential for advancing our understanding of dreams and their underlying neural mechanisms.

The development of more sophisticated and accurate techniques for dream decoding across all sensory and cognitive modalities will significantly enhance our ability to study dreams. These advancements could reduce reliance on subjective self-reports, minimizing the need to disrupt participants' sleep to gather data. Moreover, improved decoding models may enable the exploration of topics that are currently inaccessible, such as dreaming in animals or individuals in comatose states.

As neural decoding technologies advance, it is critical to consider the ethical implications of reconstructing private mental experiences. Questions surrounding privacy, consent, and the regulation of such technologies must be addressed proactively to ensure their responsible use. We urge researchers, policymakers, and ethicists to collaborate in establishing guidelines that balance scientific progress with the protection of individual rights.

By advancing dream decoding techniques and addressing the associated ethical challenges, this field has the potential to revolutionize dream research, providing profound insights into the human mind and consciousness.

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