Title:

AI Signal Processing: The Value Proposition of Enhancing Machine Vision Capabilities using The Expanded Johnson Criteria and The Psychothotonix Sphere to Model Human Perception.

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Abstract:

This paper focuses on the value and potential of utilizing electro-optical signal processing, specifically the time series integration of physical and psychophysical waves, to improve machine vision and model human perception. The concept of electro-optical signal processing using the Expanded Johnson Criteria, DRI (Detection, Resolution, Identification) Sphere and the Psychothotonix, BED (Behavior, Emotion, Decision) Sphere as representative axes is introduced. These spheres represent the evolving interpretation of image sensor data and human perception over time, forming physical and psychophysical waves. The paper explores the potential results of training a neural network with time series psychophysical data labels relative to the physical wave data. By incorporating subjective human interpretations into the training process, the neural network can learn to better analyze and understand video content, potentially improving its accuracy and ability to discern subjective viewpoints in conjunction with capturing demographic information as metadata alongside the psychophysical data labels. The utilization of psychophysical data labels in electro-optical signal processing has the potential to greatly enhance machine vision capabilities. By incorporating subjective human interpretations and demographic information into the analysis of video content, companies can improve the accuracy of their algorithms, optimize content targeting, and deliver more personalized and relevant experiences to users as well as enhance predictive capabilities.

Imagine, the electro-optical signal processing of two unit spheres with the axes listed in the order x,yz. The first sphere is an expansion of the Johnson Criteria with the axes representing Detection, Resolution and Identification ("DRI Sphere") and the second Psychothotonix sphere Behavior, Emotion and Decision ("BED Sphere"). The vector coordinates are moving in time as image sensor data and human interpretation changes relative to the images evolving. The coordinates moving in time form two waves: a physical wave of the image and a psychophysical wave of the interpretation. How does this patented technique improve machine vision?

The electro-optical signal processing technique involving the analysis of two unit spheres representing the DRI Sphere and the BED Sphere, can have valuable implications for improving machine vision. By considering both the physical wave of the image and the psychophysical wave of interpretation, this technique incorporates both objective visual data and subjective human understanding.

Here are some potential benefits and applications of this technique:

Enhanced object detection: The DRI Sphere, representing detection, resolution, and identification, can help improve the accuracy and reliability of object detection algorithms. By considering the physical wave of the image, machine vision systems can better identify and distinguish objects in various environments, even in challenging conditions.

Context-aware analysis: Incorporating the BED Sphere, which represents behavior, emotion, and decision, adds a human-centric perspective to machine vision systems. By analyzing the psychophysical wave of interpretation, the system can gain insights into the emotional state, intentions, and behaviors of individuals captured in images or videos. This contextual understanding can be valuable for applications such as surveillance, security, and human-computer interaction. It also creates a time series psychophysical data set that may be used as a training set to create a predictive tool for AI to learn to mimic human behavior, emotion and decisions from video images.

Adaptive algorithms: The dynamic nature of the coordinates moving in time allows for adaptive algorithms that can learn and evolve over time. As image sensor data and human interpretations change, the machine vision system can continuously update its models and improve its performance. This adaptability can lead to more accurate and robust vision-based applications.

Human-machine collaboration: By incorporating human interpretation into the analysis, the technique promotes collaboration between humans and machines. It allows machine vision systems to leverage human expertise and intuition, leading to more nuanced and insightful analysis of visual data. This collaboration can be particularly useful in domains such as medical imaging, where human expertise is critical for accurate diagnosis.

Bias mitigation: Considering the psychophysical wave of interpretation can help identify and mitigate biases in machine vision algorithms. Human interpretations are subject to various biases, and by analyzing these biases, we can develop techniques to address them and ensure fair and unbiased outcomes in machine vision applications.

Implementing this technique may involve significant computational and algorithmic challenges. The coordination and synchronization of the physical and psychophysical waves, as well as the integration of subjective human interpretations, require careful design and modeling. Overall, the electro-optical signal processing technique has the potential to advance machine vision by incorporating both objective and subjective dimensions, leading to more accurate, context-aware, and collaborative visual analysis systems.

Where we have two waves representing the physical wave of the image and the psychophysical wave of interpretation, we can formulate a wave equation that captures their dynamics. Let's denote the physical wave as $\psi_1(x, y, z, t)$ and the psychophysical wave as $\psi_2(x, y, z, t)$, where (x, y, z) represents the spatial coordinates and t represents time.

The wave equation for each wave can be represented as follows:

1. Physical Wave (ψ_1):

   $\nabla^2\psi_1 - (1/v_1^2)\, \partial^2\psi_1/\partial t^2 = 0$,

   where ∇^2 is the Laplacian operator, v_1 represents the velocity of the physical wave, and $\partial^2\psi_1/\partial t^2$ represents the second partial derivative of ψ_1 with respect to time.

2. Psychophysical Wave (ψ_2):

   $\nabla^2\psi_2 - (1/v_2^2)\, \partial^2\psi_2/\partial t^2 = 0$,

   where ∇^2 is the Laplacian operator, v_2 represents the velocity of the psychophysical wave, and $\partial^2\psi_2/\partial t^2$ represents the second partial derivative of ψ_2 with respect to time.

These wave equations describe the propagation and evolution of the physical and psychophysical waves in the given scenario. The Laplacian operator (∇^2) describes the spatial variations, while the second partial derivative with respect to time ($\partial^2/\partial t^2$) captures the temporal changes.

It's important to note that the specific forms and parameters of these wave equations (e.g., the velocities v_1 and v_2) would depend on the characteristics of the physical and psychophysical waves in the electro-optical signal processing context. These equations provide a general framework for understanding the wave-like behavior of the two waves involved in modeling human perception.

If you were training a neural network with time series psychophysical data labels relative to the physical wave data, there are several potential anticipated results:

Improved prediction accuracy: By incorporating psychophysical data labels, which capture the subjective human interpretation of the physical wave data, the neural network may achieve improved prediction accuracy. The inclusion of subjective information can provide additional insights and context that can enhance the network's ability to understand and interpret the visual data.

Context-aware predictions: The neural network, trained on the relationship between the physical wave data and psychophysical labels, may become more context-aware in its predictions. It can learn to recognize patterns in the physical wave data that are associated with specific psychophysical responses. This context-awareness can be valuable in applications where the interpretation and understanding of visual data rely on subjective human factors, such as emotion recognition or behavior analysis.

Human-like interpretation: Since the psychophysical data labels represent human interpretation, the trained neural network may exhibit patterns of interpretation similar to those of humans. This could lead to predictions and classifications that align more closely with how humans perceive and interpret visual information.

Reduced bias: Training the neural network with time series psychophysical data labels can help mitigate bias in the machine vision system. By incorporating subjective human interpretations, the network can learn to account for diverse perspectives and minimize biases that may be present in the physical wave data alone. This can lead to fairer and more unbiased predictions and decisions.

Challenges with subjective variability: One challenge in training a neural network with psychophysical data labels is the inherent variability in subjective interpretations. Human interpretations can differ based on individual differences, cultural factors, and other subjective biases. As a result, it may be more challenging to achieve consistent and reliable training performance compared to purely objective data labels.

Data availability and labeling complexity: Acquiring and labeling psychophysical data can be more complex and time-consuming than labeling purely objective data. Collecting subjective interpretations from human observers and ensuring reliable annotations can require careful experimental design and rigorous data collection protocols.

When dealing with time series wave data from the DRI Sphere and BED Sphere, several signal processing algorithms can be useful for analysis and extraction of meaningful information. A few examples are:

Fourier Transform: The Fourier Transform is a fundamental algorithm used to analyze the frequency content of a signal. By applying the Fourier Transform to the time series wave data, you can decompose the signal into its constituent frequency components. This can help identify dominant frequencies, periodic patterns, or harmonic relationships within the DRI and BED waveforms.

Wavelet Transform: The Wavelet Transform is a versatile tool that analyzes signals across both time and frequency domains. It is particularly useful for capturing localized, transient, or non-stationary features in the time series data. By applying the Wavelet Transform, you can extract time-frequency representations of the DRI and BED waveforms, revealing relevant temporal and spectral characteristics.

Time-Frequency Analysis: Time-Frequency analysis techniques, such as Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), or Wigner-Ville Distribution (WVD), offer a more detailed examination of how the frequency content of a signal evolves over time. These techniques can help identify changes in spectral characteristics or time-varying patterns within the DRI and BED time series wave data.

Empirical Mode Decomposition (EMD): EMD is a data-driven algorithm that decomposes a signal into its intrinsic mode functions (IMFs). It is particularly effective for analyzing non-linear and non-stationary signals. By applying EMD, you can decompose the DRI and BED waveforms into their constituent IMFs, which represent different scales or oscillatory modes present in the data.

Feature Extraction Techniques: Various feature extraction algorithms can be employed to capture specific characteristics of the DRI and BED waveforms. Examples include statistical features (mean, variance, skewness), energy-based features (signal power, spectral entropy), or time-domain features (autocorrelation, zero-crossing rate). These features can be used to quantify and represent key aspects of the waveforms for subsequent analysis or classification tasks.

Machine Learning Techniques: Once relevant features have been extracted from the DRI and BED wave data, machine learning algorithms can be applied for classification, prediction, or anomaly detection. Techniques such as support vector machines (SVM), random forests, recurrent neural networks (RNN), or convolutional neural networks (CNN) can be used to build models that learn patterns and relationships in the time series data and make predictions or classifications based on them.

The specific choice of signal processing algorithms depends on the characteristics of the DRI and BED wave data, the desired analysis objectives, and the available computational resources. It's important to experiment with different algorithms, consider the limitations and assumptions of each technique, and validate the results against ground truth or domain knowledge to ensure the meaningful interpretation of the time series wave data.

If demographic information is captured as metadata relative to the psychophysical data labels, it can provide additional descriptiveness that can assist in generating media content with a higher conversion rate and targeting media towards specific demographics, including advertising.

Precise targeting: By incorporating demographic information such as age, gender, location, or other relevant factors, advertisers can better understand the preferences and characteristics of specific demographic groups. This information can assist in tailoring and targeting media content and advertisements to those specific demographics, increasing the relevance and effectiveness of marketing campaigns.

Personalization: The combination of psychophysical data labels and demographic metadata enables personalized advertising and content recommendations. By considering both subjective interpretations and demographic factors, advertisers can deliver content that resonates with individuals on a more personal level. This can enhance user engagement and improve the overall user experience.

Improved advertising effectiveness: With the ability to target specific demographic groups more accurately, advertisers can optimize their advertising campaigns. By aligning the content and messaging of advertisements with the psychophysical interpretations and demographic profiles of the target audience, advertisers can increase the likelihood of capturing attention, generating interest, and driving desired actions.

Minimized ad waste: Targeting media towards specific demographics using psychophysical data labels and demographic metadata can help minimize ad waste. Advertisements can be directed towards the audiences that are most likely to be interested in the content, reducing irrelevant or untargeted exposure. This can lead to cost savings and a more efficient allocation of advertising resources.

Ethical considerations: When using demographic information for targeting media, it is crucial to handle this data with appropriate ethical considerations. Advertisers must ensure compliance with privacy regulations and obtain appropriate consent for data collection and usage. It is important to protect individuals' privacy and use demographic information responsibly to avoid discriminatory practices or biases.

Overall, the integration of demographic information as metadata relative to psychophysical data labels can enhance the targeting capabilities for media, including advertising, enabling more personalized and relevant content delivery to specific demographic groups increasing conversion rates.

Related Works:

* "Quantum Psychothotonix," The measurement and control of human perceptions and related human behavior patterns based on space-time imaging., Deep AI, 2021 (Co-Authored, Dr. Richard Conner).

* "PT Vectors & Tensors," PSYCHOTHOTONIX defines a quantum data set of internal non-matter image states consisting of (B)ehavior (E)motion and (D)ecision in the human brain as vectors mapped to a Psychothotonix sphere moving in time., Deep AI, 2021 (Co-Authored, Dr. Richard Conner)

* "Object Image Classification: Expanding the Johnson Criteria, Detection, Resolution, and Identification as Axes on a Sphere, Integrating a Systems Modulation Transfer Function," Unpublished, 2023 (Co-Authored, Dr. Richard Conner, Dr. Daniel Winterhalter)