Literature Review

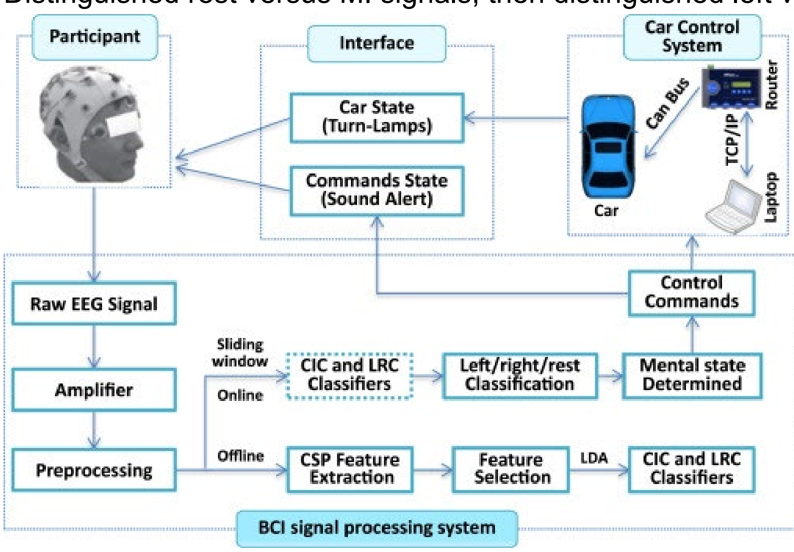
How to post:

1. Check if someone else has posted the paper.
2. Paste the title of the paper.
3. In bullet points, paste the doi (ask if you can't find it) and publication date.
4. In more bullet points, summarize significant takeaways from the paper including methods used, challenges, and relevance to our project.

You may need to use the campus VPN in order to access the papers.

The first few are pulled from searching "brain controlled car" in scholar.google.com.

"Toward brain-actuated car applications: Self-paced control with a motor imagery-based brain-computer interface"

- https://doi.org/10.1016/j.compbiomed.2016.08.010
- 2016
- Used motor imagery (MI) to control car
- Distinguished rest versus MI signals, then distinguished left versus right tasks
- 

- Passband: 8-34 Hz
- Offline training of classifiers -> online application of classifiers, data processed every 100 ms with 100 ms sliding window

"Design of Brain Controlled Robotic Car using Raspberry Pi"

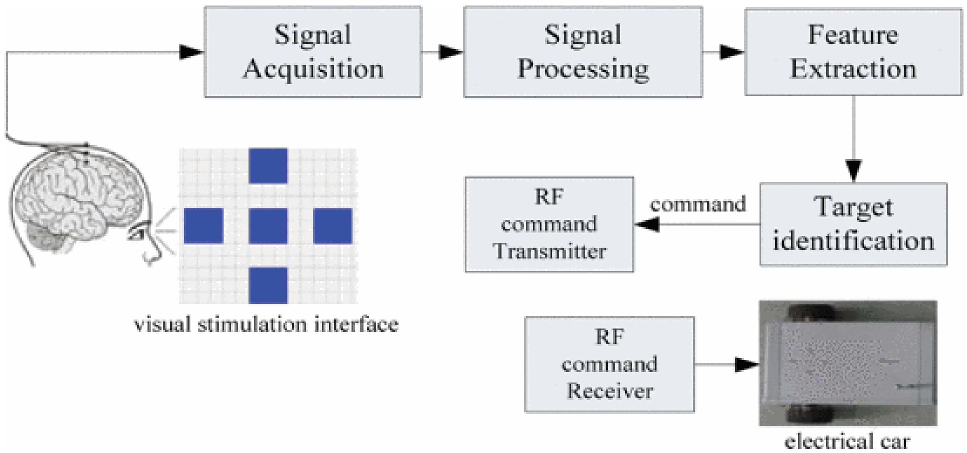
- https://doi.org/10.1109/ICOEI51242.2021.9452957
- 2021
- Not very in depth, don't use

"EEG-based asynchronous BCI control of a car in 3D virtual reality environments"

- https://doi.org/10.1007/s11434-008-0547-3
- 2009

- Uses virtual environment to test cars
- Uses motor imagery
- Paywall :(

"Remote control of an electrical car with SSVEP-Based BCI"

- https://doi.org/10.1109/ICITIS.2010.5689710
- 2010
- 

- Visual interface in order to distinguish intent
- Average signals and FFT used for feature extraction
- Not too much on the electrical car

"The control of a virtual automatic car based on multiple patterns of motor imagery BCI"

- https://doi.org/10.1007/s11517-018-1883-3
- 2019
- Usage of left hand, right hand, foot, and both hands motor imagery
- Passband: 8-30 Hz
- Motor imagery -> changes in passband
- Common average reference (CAR) filtering
- SVM used to classify signals
- Acceleration, deceleration, turning right, turning left

"Current status, challenges, etc of BCI"

- doi: 10.3389/fnbot.2020.00025
- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7283463/

"Noninvasive neuroimaging enhances continuous neural tracking for robotic device control"

- Doi: 10.1126/scirobotics.aaw6844
- https://www.science.org/doi/10.1126/scirobotics.aaw6844

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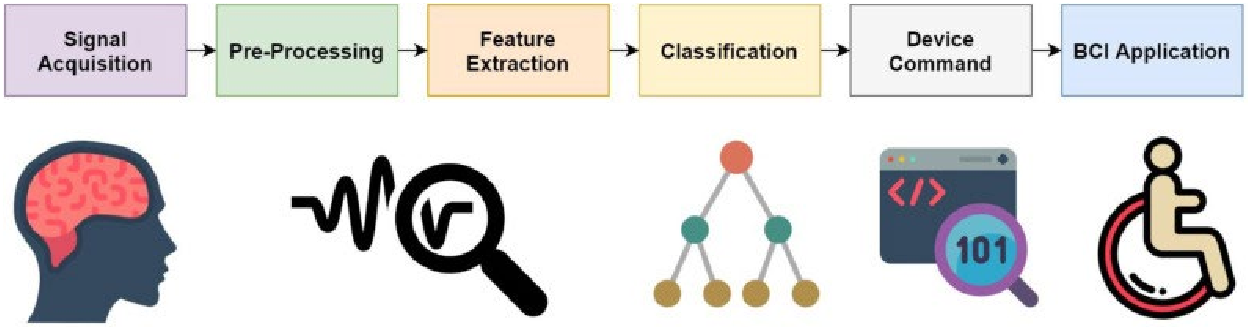
- 

- Synchronous v asynchronous BCI, former is easier to build and more user-friendly, asynchronous generates mental task for BCI to complete at certain time
- Different types of potentials: movement-related cortical potential, error-related potential, slow cortical potential, steady state evoked potential; each have different purposes relating to what brain wants the body to do
- BCI that are real-time need removal methods that are automatic, the filtering methods can be automatically executed when they are given a reference signal
- Will need many reference signals, the more we have, the better
- Autoregressive modeling = “linear regression of the current observation of the series against one or more earlier observations.”
- Classification Methods: support vector machine, neural network, linear discriminant analysis, bayesian classifier, k-nearest neighbor, and deep learning approaches (described in depth in article)
- Performance evaluation: receiver operating characteristics and area under the curve
- Challenges: some modalities have signal processing issues, sometimes because of the nature of EEG signals (artifact prone, extremely nonlinear and nonstationary)
    - Too long of calibration period for specific candidate, not realistic results to use on a random person
    - Lack of adequate data analysis methods, some have more limitations than others
    - No standard performance evaluation amongst community

“Evaluating If Children Can Use Simple Brain Computer Interfaces”

- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6369154/
- doi: 10.3389/fnhum.2019.00024
- measure signals using cohen’s kappa, goes under ML
- cohen’s kappa: relates to raters (quantitative to qualitative)
- lot of info on the trial itself

“A passive BCI for monitoring the intentionality of the gaze-based moving object selection”

- https://iopscience.iop.org/article/10.1088/1741-2552/abda09
- doi:10.1088/1741-2552/abda09
- moving ball, moving window of 867 ms in length
- filtered with zero-phase lowpass 4th order Butterworth filter, cutoff frequency =30Hz
- used linear discriminant analysis

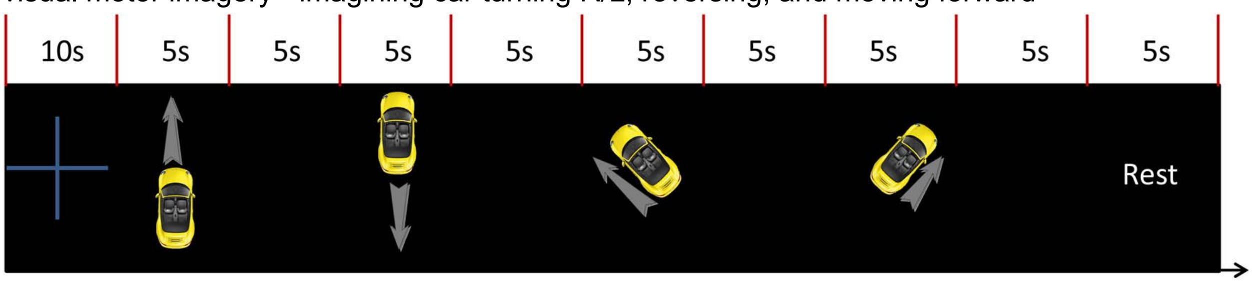
"Milo: The Brain-Controlled Wheelchair"

- McGill NTX Github
- eye blink = start, jaw clench = stop
- 250 Hz, 2s window
- PSD to extract mu and beta band power

"Brain Computer Interface for Controlling RC-Car Using Emotiv Epoc+"

- 2018
- 14-channel EEG
- SSVEP
- 12-20 Hz pass-band
- SVM classification of left, right, and forward signals using visual stimulus

"A novel strategy for driving car brain–computer interfaces: Discrimination of EEG-based visual-motor imagery"

- https://doi.org/10.1515/tnsci-2020-0199
- 2021
- visual motor imagery - imagining car turning R/L, reversing, and moving forward
- 

- Correlation between channels calculated for each motion
- Online implementation not tested

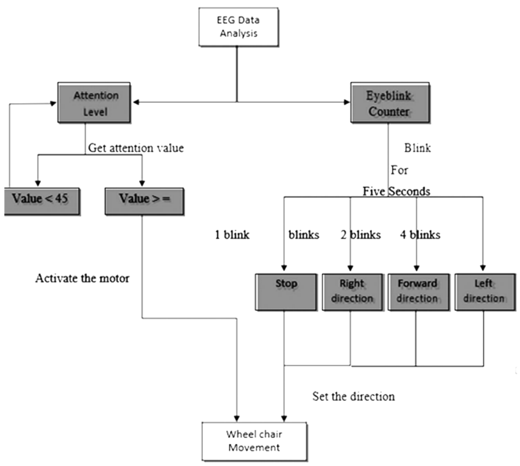
"A Brain Controlled Wheelchair to Navigate in Familiar Environments" (2010)

- https://ieeexplore.ieee.org/document/5462915;
- DOI: 10.1109/TNSRE.2010.2049862
- Uses a slower BCI for destination selection and a faster BCI for stopping the wheelchair's motion
- User selects a typical location in a known environment (ex. kitchen, bedroom, bathroom) → wheelchair movement is restricted to predefined paths that connect these locations
    - Offers users limited options for safety purposes and to avoid stressing them out
- Drawbacks: can only be used in specific environments; not adaptable to change
- Used a P300-based BCI for users to select one of nine predefined destinations
    - Is a slower BCI, but it requires no training, has stable performance, and can be used by people with severe disabilities
- Remove artifacts from EEG signal → filtering → downsampling → segment into epochs → produces a feature vector to be input into an SVM algorithm for classification
- Two faster BCIs for successful stopping: faster P300 and a BCI based on motor imagery
    - Faster P300 requires no training; motor imagery BCI requires extensive training

- Addressing obstacles: wheelchair automatically stops within 50 cm of obstacles (sensors detect) → interface returns to the menu to select a destination
- BCI performance metrics: response time, false activation rate, error rate, mission time, concentration time
- Results: users spend 15s on average to select a destination; can stop the wheelchair within 5s on average (requires 1.5m distance at 0.5m/s velocity)

"Research and Development of a Brain-Controlled Wheelchair for Paralyzed Patients" (2021)

- https://www.techscience.com/iasc/v30n1/43950; DOI: 10.32604/iasc.2021.016077



- Wheelchair motor is activated by a specific increase in the user's brain activity
- Wheelchair direction is specified by performing a specific blinking sequence
- FFT analysis was conducted to remove artifacts and noise from the data
- The "level analyzer method" was used to extract attention and blinking data
- Methods to reduce signal-to-noise ratio: CSP, PCA, CAR
- User can switch between automatic control (ex. obstacle avoidance) and subject control

"Review of the State-of-the Art of Brain-Controlled Vehicles" (2021)

- https://ieeexplore.ieee.org/document/9499083; DOI: 10.1109/ACCESS.2021.3100700
- Brain-Controlled Vehicle (BCV) objectives: navigation, staying in your lane, passing other cars, turning, avoiding obstacles, braking in different situations
- Brain-Controlled Aerial Vehicle (BCAV) objectives: same as BCV + takeoff and landing
- Biosignals to control vehicles: EEG, EOG, EMG
- The sensorimotor cortex controls intended movements → important EEG patterns: ERP, ERD/ERS, LEP, SSVEP, RP
- Brain signal processing steps: preprocessing, feature extraction, optimization, feature selection, classifiers, statistical analysis, real-time experiments

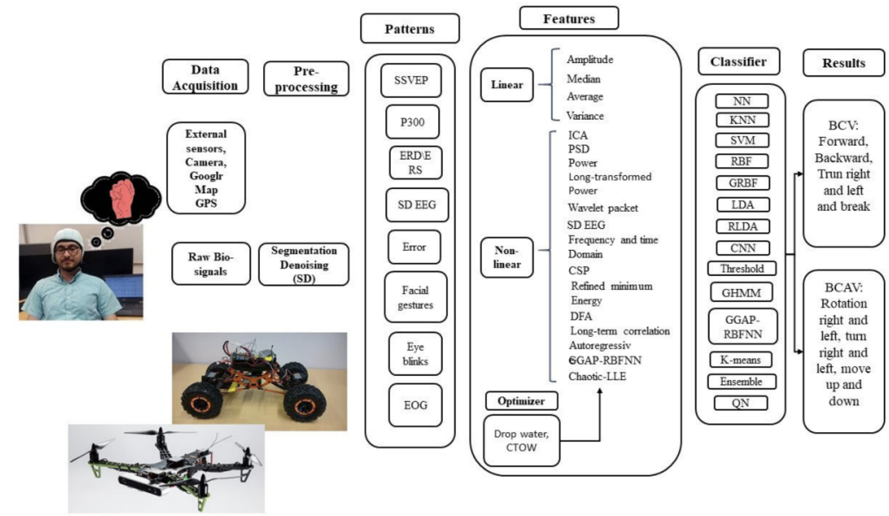


FIGURE 1. Algorithm's (features and classifiers) diagram for identifying the driver's intention for BCV and BCAV applications.

"Review of Machine Learning Techniques for EEG Based Brain Computer Interface" (2022)

- https://doi.org/10.1007/s11831-021-09684-6
- Looked at multiple machine learning techniques for classification of motor imagery, P300, and SSVEP signals
- Process: learning algorithm is used to learn rules, which is then fed into a classification model, and gets output
- Motor imagery: classification algorithms used to convert extracted features into distinct motor tasks (hand gestures, foot movements, word generation, etc)
- P300: part of the electroencephalogram (shows spontaneous electrical activity of brain), shows up after the experience of significant auditory, and visual stimulus
    - Generally have higher information transfer rate than motor imagery
    - Tend to be used in spellers, smart devices, wheelchairs
    - Requires a large amount of training
- SSVEP: form of brain response that is described by a frequency pattern at the stimulus frequency as well as its harmonic frequencies
    - Performs better than P300 and motor imagery
    - High information transmission rate and little to no training required

"IoHT-based deep learning controlled robot vehicle for paralyzed patients of smart cities" (2022)

- https://doi.org/10.1007/s11227-021-04292-4
- Developed unmanned robot vehicle to improving daily life routines for paralyzed patients, used EEG data for better communication with a robotic system
    - Controlled by deep learning model, used EEG signals
        - Had 99.5% success rate and 0.5% loss rate
    - Data received were used to predict the action of the unmanned robot vehicle
- Developed smart city framework for robot to have a communication system with a flexible system

    - Is able to connect with emergency departments (hospital, fire, police) when patient needs immediate help/action as well as friends/family
    - Gives patients more detailed communication methods to express their needs

"Classification of Motor Imagery EEG Signals with Support Vector Machines and Particle Swarm Optimization"
- https://doi.org/10.1155/2016/4941235
- 2016
- SVM with parameters chosen via particle swarm optimization
- Details CSP algorithm

Deep Learning Enabled Semantic Communication Systems
- https://ieeexplore.ieee.org/document/9398576
- Transmission of symbols
- We could use symbols to help control the vehicle

"Review of the State-of-the-art on Bio-signal-based Brain-controlled Vehicle"
https://doi.org/10.48550/arXiv.2006.0
2937

- Controlled using bio-signals (EEG, electrooculogram, electromyogram)
- Pick up patterns in motor imaginary cortex area (specifically the area that detects intention)
    - Event related desynchronization and/or synchronization
    - Event Related Potentials (ERPs)
    - Patterns appear prematurely in EEG (0.5-2 seconds earlier than reflected action)
- Ways to measure:
    - ERD/ERS patterns (cognitive patterns that appear after intending to move and if the intention becomes an action)
    - SSVEP pattern - response pattern that appears when visual stimuli is provided
    - ERP pattern - measured electrophysiological response by EEG to specific stimulation
    - RP pattern - generated before real movement by about 1-1.5 seconds

SSVEP-Based BCIs
- 10.5772/intechopen.75693
- "sinusoidally modulated monochromatic light"
- frequency of light > 6 Hz
- Oz, O1, O2, PZ, P3, P4,
- 4-60 Hz
- Resonance phenomenon observed 10, 20, 40, 80 Hz
- Feature extraction

    - ICA
    - FFT
    - CWT
    - HHT
- Feature classification
    - Bayesian classifier
    - LDA
    - SVM
    - k-NNC
- Black background
- 7, 11, 9, 13 Hz

Independent component analysis for a low-channel SSVEP-BCI

A classification algorithm of an SSVEP brain-Computer interface based on CCA fusion wavelet coefficients