Motivation
- Traditional robotic mapping assumes that uncertainty originates from sensor noise and filters out conflicting measurements
- Instead of treating conflicting observations as outliers, we can use them to learn about the nature of environmental changes.
- Explicit modelling of the changes improves mobile robots’ ability to operate reliably for long periods of time [8,9].

Frequency Map Enhancement
- Can identify reoccurring patterns from long-term observations and use them to predict the future environment states.
- Based on non-uniform Fourier transform techniques.
- Applies to any environment model comprises of binary states.
- The uncertainty of a state is model as a probability in time:
  \[ p(t) = p_0 + \sum_{j=1}^{N} p_j \cos(\omega_j t + \varphi_j) \]  
  (1)
- The parameters of Equation (1) can be obtained from observations of the state \( s \) at times \( t_k \) by a non-uniform Fourier transform:
  \[ S(\omega) = \sum (o(t_k) - p_0) e^{-j2\pi \omega t_k} \]  
  (2)
- **Example:** week-long observation of an office door.

Introduction
- A novel method that introduces the notion of dynamics into traditional environment models meant for static scenes.
- Represents the probabilities of binary environment states by the most prominent components of their frequency spectra.
- Improves mapping [1], localization [2,3], planning [4,5] and allows spatio-temporal exploration [6,7] of changing environments.

FreMEn: Frequency Map Enhancement for Long-term Mobile Robot Autonomy in Changing Environments

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FreMEn for visual localization
- Long-term observation of a feature’s visibility (centre) is transferred to spectral domain (left). The most prominent spectral components (left) are selected and transferred back to the time domain (center).
- This equation represents the probability of the feature’s visibility over time (centre, right), and can predict its appearance (right).
- This allows to obtain time-specific feature maps for visual topological localization, improving long-term autonomy.

References

Indoor experiments
- Training: A SCITOS-G5 robot captured 8000 images of 8 locations every 10 minutes for 7 days.
- Testing: 2 additional day-long datasets consisting of 1000 images were collected after 1 week and after 3 months.
- Captures changes caused by illumination and human activity.

Outdoor experiments
- Training: A P3AT mobile robot captured images of 5 locations every month over a period of one year.
- Testing: 3 additional data collection runs during the following year.
- Captures environment changes induced by seasonal factors.

Ongoing work
- Applying FreMEn to the BRIEF feature descriptor results in time-dependent image feature method.
- Preliminary experiments indicate improvements in robustness to seasonal changes.

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