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

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***Abstract*—We present a method for introducing representation of dynamics into environment models that were originally tailored to represent static scenes. Rather than using a fixed probability value, the method models the uncertainty of the elementary environment states by probabilistic functions of time. These are composed of combinations of harmonic functions, which are obtained by means of frequency analysis. The use of frequency analysis allows to integrate long-term observations into memory-efficient spatio-temporal models that reflect the mid- to long-term environment dynamics. These frequency-enhanced spatio-temporal models allow to predict the future environment states, which improves the efficiency of mobile robot operation in changing environments. In a series of experiments performed over periods of days to years, we demonstrate that the proposed approach improves localization, path planning and exploration.**

I. Introduction

As robots gradually enter human-populated environments, they have to deal with the fact that the environments are uncertain because they change over time. While the probabilistic mapping methods used in mobile robotics have proven their ability to handle uncertain and incomplete environment knowledge, their theoretical foundations assume that the uncertainty is caused by sensor noise rather than by natural processes that are behind the environment changes. The static world assumption negatively impacts the ability of these models to properly reflect the environment dynamics and effectively support long-term autonomous operation of mobile robots. The authors of articles [1], [2], [3], [4], [5] have already demonstrated that explicit modeling of the environment changes improves mobile robot localization.

The paper presented in [5] represents the world dynamics by multiple maps with different timescales, which are switched on the fly based on their consistency with the current sensory readings. The authors of [6] present a system that evaluates the persistence of visual features over time in order to identify features that are more likely to be stable. Another approach [1] demonstrates that clustering spatially-close observations into 'experiences' improves long-term localization. The article [3] associates each cell of an occupancy grid with a hidden Markov model, which improves the localization robustness as well. Kucner's method [7] assumes that occupancies of grid cells are influenced by a moving objects, which allows to infer typical motion patters in a given environment. Finally, Sünderhauf's method proposes to learn typical appearance changes caused by seasonal factors and use this knowledge for long-term predictions of environment appearance [4].

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'Change is the essential process of all existence,' Mr. Spock, stardate 5730.2

Our approach to this problem is based on the assumption that some of the mid- to long-term processes that cause the environment changes are (pseudo-)periodic, e.g. seasonal foliage variations, daily illumination cycle or routine human activities. To reflect this assumption, we represent the probability of each local environment state not by a single value, but by a probabilistic function of time composed of several harmonic functions whose periodicities and amplitudes relate to the frequencies and influences of these hidden processes.

II. Method Description

The proposed method, coined the Frequency Map Enhancement (FreMEn), represents the probability of each environment state by a function of time

$$p(t) = p_0 + \sum_{j=1}^{n} p_j \, cos(\omega_j \, t + \varphi_j), \tag{1}$$

where n is the number of environment processes taken into account, ω_j, φ_j and p_j relate to the frequencies, time offsets and influences of these processes, and p_0 is the mean probability of the state. To obtain the parameters ω_j, φ_j and p_j, we analyse the long-term observations of each environment state by means of a (non-uniform) Fourier transform. In short, assuming that the state $s(t)$ has been measured at regular intervals, we first obtain the state's frequency spectrum as

$$S(\omega) = \mathcal{FFT}(s(t)), \tag{2}$$

where $\mathcal{FFT}(.)$ stands for the Fast Fourier Transform. The parameters ω_j, φ_j and p_j in Equation (1) are equal to the aplitudes, phases and frequencies of n most prominent spectral components of $S(\omega)$. However, Equation (2) assumes that the state $s(t)$ is measured on a regular basis, which cannot be satisfied in real-world scenarios. In realistic scenarios, one has to employ a non-uniform Fourier Transform, such as the one mentioned in [8] or [9].

The approach, which was originally presented at [10], can be applied to all environment models that represent the world as a set of independent component with binary states. In particular, its application to occupancy grids allows to compress long-term observations [11], its use with topological maps improves robotic search [12] and path planning [13], and frequency-enhanced feature maps have shown to improve robustness of long-term visual localization [2]. Moreover, the time-dependent probability of the environment states expressed by Equation (1) allows the calculation of the spatio-temporal environment entropy, which, combined with information-theoretic planning, results in life-long spatio-temporal exploration of dynamic environments [9], [14], [15].

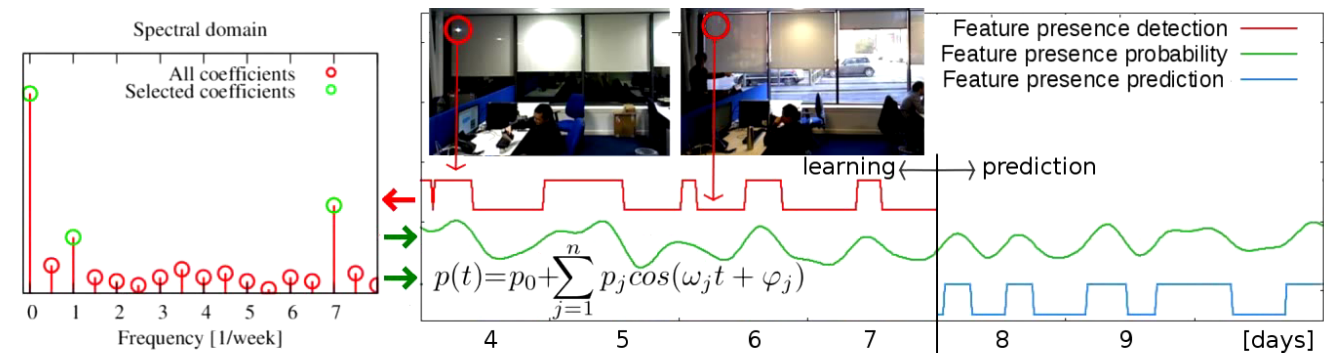

Fig. 1. Frequency-enhanced feature map [2] for visual localization: The observations of image feature visibility (centre,red) are transferred to the spectral domain (left). The most prominent components of the model (left,green) constitute an analytic expression (centre,bottom) that represents the probability of the feature being visible at a given time (green). This allows to predict the feature visibility at a time when the robot performs self-localization (blue).

III. FreMEn for visual localization

To evaluate the usefulness of the approach, we apply it to the problem of visual-based localization in changing environments. Here, the environment representation is composed of several local maps that consist of collections of visual features visible at the particular locations. The visibility of the individual image features [16] over time is represented by FreMEn, which allows to predict their visibility for a particular time and use the time-specific features for visual localization. The experiments were performed both indoors and outdoors. The indoor experiment was performed at Lincoln Centre for Autonomous Systems, where a SCITOS-G5 robot captured color images of 8 designated areas every 10 minutes for one week and used the models created to localize itself during one day of the following week. The outdoor experiment was performed in the Stromovka urban park in Prague, where a P3AT robot captured color images of 5 designated places on a monthly basis for one year and used the dynamic feature map to determine its location during three independent runs during the following year. While the indoor dataset was influenced by the daily illumination cycle and human activities in the office, (see Figure 1), the outdoor dataset captured seasonal variations of foliage, see Figure 2.

Fig. 2. Seasonal environment variations captured by the outdoor dataset.

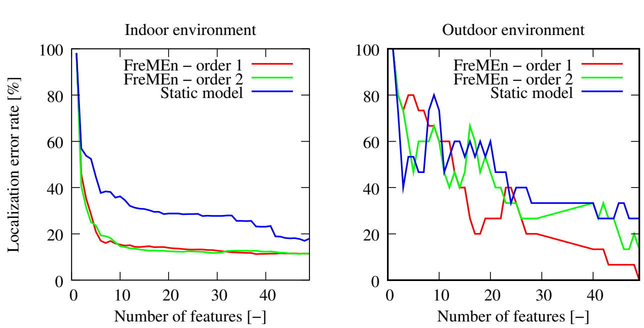

Fig. 3. The dependency of localization error on the number of features used.

The dependence of the localization error on the number of features used is shown on Figure 3, which indicates that the frequency-enhanced models that generate a set of likely-visible features for a particular time outperform the 'static' approach that relies on the most stable features. These results indicate that modelling the appearance of dynamic environments by our approach improves the robustness of localization.

The presented approach can be also applied to individual binary comparisons of the BRIEF [16] descriptor. The frequency-enhanced feature descriptor would consist of binary comparions that are relevant to the given temporal context, which would improve its distinctiveness in long-term scenarios.

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