are shown respect to the Victoria Park [4] and Alcazar of Seville [10] datasets.

II. RELATED WORK

Graph SLAM has multiple highly efficient optimization solutions. iSAM [4] converts the graph SLAM maximum likelihood estimate into a non-linear least squares optimization problem. The factor graph is incrementally solved by numerical methods, obtaining real-time performance and Bayesian smoothing accuracy. These optimization techniques show the effectiveness of the factor graph formulation of the SLAM problem, and we base our formulation on similar formulations.

A known solution to SLAM in dynamic environments is to maintain two occupancy maps modeling the dynamic and static parts of the environment [14]. By differentiating dynamic and static parts of the environment with different representation, this method is capable of mapping and localization in dynamic environments over time. An alternative approach of dealing with moving objects in dynamic environments is combining SLAM with object detection and tracking. Wang et al. [13] proposed a Bayesian framework to solve the SLAM together with object motion modeling by sophisticated object detection and tracking and data association algorithms. In this approach, object detection and tracking is used as a preprocessing front-end to filter out moving objects.

Robust SLAM techniques have been proposed to solve front-end outlier problems without relying on pre-filtering. Some use robust objective functions or robust representation of observations. Dynamic Covariance Scaling [1] adds a robust kernel factor to regularize the Mahalanobis errors in the Gaussian distributions of landmark observations. Max-Mixture [7] enhances factor potentials with a clever representation for mixtures of Gaussians in place of a unimodal Gaussian distribution. This kind of approaches still assume sources of errors being mostly perceptual aliasing in wrong loop closures, without regard to environmental movement. Unless modeled explicitly in factor potentials, these methods will have difficulty in handling the movement of landmarks.

Front-end outliers and dynamic elements can also be addressed through identifying mobility as part of the back-end graph optimization framework. Haehnel et al. [3] and Rogers et al. [11] extend graphical model formulations with a latent indicator variable to infer whether a landmark is mobile. EM algorithms are used to iteratively infer these latent landmark mobility variables in the graphical model and estimate the optimal SLAM solution. The switchable constraints [12] approach allows the optimizer to naturally change the topological structure of the problem during the optimization itself using switch variables as a multiplicative scaling factor on the information matrix associated with that constraint. However, these EM based algorithms lack the robustness provided by previous techniques. Further, an observation-based indicator only models the observation it associates with and will not characterize the mobility of landmarks which associate with multiple observations.

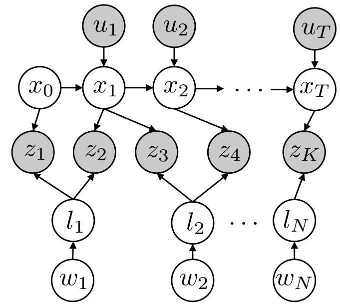

Fig. 2: Graphical Model Formulation. Dark nodes are observed.

III. MODEL: AUGMENTED GRAPH SLAM

Following [4] we formulate the SLAM problem in graphical models as in Figure 2. Specifically, the robot states (as position and orientation over time in map coordinates) are denoted by $X = \{\boldsymbol{x}_i\}$ with $i \in 0, \dots T$, the landmark locations in map coordinates by $L = \{\boldsymbol{l}_j\}$ with $j \in 1, \dots, N$, the control inputs for movement by $U = \{\boldsymbol{u}_i\}$ for $i \in 1, \dots, T$ and the landmark measurements in robot coordinates by $Z = \{\boldsymbol{z}_k\}$ with $k \in 1, \dots, K$. In addition to the classical graph SLAM formulation, we augment the representation of landmarks with a set of N scalar latent parameters $W = \{w_j\}$ with $j \in 1, \dots, N$. At each time k, the measurement $\boldsymbol{z}_k$ corresponds to robot pose $\boldsymbol{x}_{i_k}$, landmark $\boldsymbol{l}_{j_k}$, and latent variable w_{j_k}, where i_k associates robot poses with measurements, and j_k associates landmarks with measurements.

In considering dynamic environments, W models the mobility of each landmark about whether it is capable of movement or not without considering extra kinematics, and robustify the observation term of the model in Equation 4. Through W, corrupted measurements associated with moving landmarks are suitably eliminated as outliers from the mapping process. It may be appealing to model a dynamically moving object as a sequence of variables. However, it is shown in the following that the scalar mobility variables are adequate enough to eliminate moving landmarks from graph optimization.

According to the proposed graphical model, we give the joint probability of all variables and measurements as:

$$P(X, L, U, Z, W) \propto \prod_i P(\boldsymbol{x}_i | \boldsymbol{x}_{i-1}, \boldsymbol{u}_i) \prod_k P(\boldsymbol{z}_k | \boldsymbol{x}_{i_k}, \boldsymbol{l}_{j_k}, w_{j_k}). \quad (1)$$

Then the maximum likelihood (ML) estimate of the unobserved poses X and landmarks L given observations Z, known controls U, and the current latent parameters W are defined as

$$X^*, L^* = \arg\max_{X,L} P(X, L, U, Z, W). \quad (2)$$

To calculate the ML estimate, the objective is linearized and converted into a linear least squares problem in this form $\arg\min_{\boldsymbol{\delta}} ||\boldsymbol{A}\boldsymbol{\delta} - \boldsymbol{b}||^2$ by algebraic manipulation, and