The prevailing state-of-the-art methods for exploration in Reinforcement Learning rely on mechanisms that operate on individual steps, perturbing them with samples from random noise sources. However, these exploration mechanisms are often inadequate for many tasks. Escaping local optima in policy space sometimes requires more sophisticated policy modifications than those achievable by merely overlaying Gaussian Noise, leading to a convergence of our policy into one that yields only mediocre performance. Episodic approaches, such as those employing Movement Primitives (MPs), provide enhanced exploration capabilities. They function within the parameter space of the chosen MP, facilitating more consistent trajectory modifications. However, methods based on MPs frequently display reduced sample efficiency, stemming from their restricted ability to utilize step-based feedback effectively. Additionally, they usually have more degrees of freedom than the action space they operate in and introduce an extra layer of abstraction that the neural network must go through to interact with the environment. Consequently, our objective is to explore novel exploration approaches, striving to achieve the comprehensive exploration typical of episodic methods, but applied to step-based policies. In doing so, we aim to surmount the challenges inherent in Step-Based RL without resorting to an MP-based framework.