XI. Related Work

The idea of transforming a signal into another more suitable to analysis is well-understood as for example on time-frequency domain transforms (more amenable to analysis), signal compression (i.e., more compact yet more difficult to analyze), transmission coding (more resilient to error), and signal filtering (i.e., more compact and more suitable to analysis). The idea here however deals with multiple conflicting requirements, on which the signal is transformed into a more compact yet faithful within a relative error bound suitable for analysis. Simplify this w.r.t. arguments introduced throughout the paper, or just limit to short and sweet references to the point on each reference that must be integrated. A great deal of forecasting work has been done in the area, however, much has concentrated on accuracy and not on the temporal stability constraining of the results. [**VIDEO TRACKING**] Forecasting approaches typically operate on the unconstrained end of the temporal stability constraint, that is, no stability constraint is imposed over the generation of the forecasts. As stability constraints are imposed over forecast generation, what we refer here as the fundamental frequencies of the hidden random process are estimated/approached/played with. The error is tradeoff for goal-constrained approximations to temporal stability, however, there exists a resolution for a set of parameters beyond it, such parameters can not reduce such fractality/error tradeoff further and for which gains are not longer linear but sub-linear. For an ergodic signal, by definition, optimally one process state exists around which white noise exists. For temporally stable signals, an unknown number of such states exist, around which approximately white noise exists. The extraction of harmonic process state segments may be conceptualized to be similar to background filtering from video, where background typically has temporal stability across a time segment lasting seconds to minutes (semi-ergodic for normal video or long term (i.e., ergodic) for surveillance video). Therein, the approach is based on identifying stationariness at the pixel level w.r.t. adjacent time indexes. This application is illustrative of the timescale concerns of interest. The hidden random process is the collection of video image, which operates at a sub-millisecond scale, whereas sampling, of video images occurs at video frame scale, and analysis across longer term horizons (seconds to minutes). Heavy tail outliers have low probability and thus high information content and thus cannot be obviated in process reconstruction. For the handling of heavy tail outliers, a separate outlier signal ***‹ô(i)›*** is used. This signal identifies and provides referential context for the outlier identification. The approach uses a recursive formulation for adaptive parameter estimation w.r.t. testing the presence of temporal stability and the generation of forecast values which is highly efficient. The approach has unusually low computational complexity lower bound of ***O(1)*** –although in each operation, technically, the windowed the weight of up to ***m+m’*** samples are factored in. The **HPS** constraints the forecast problem to a dual goal of error and state FRACTALITY constraintment, on which error is tradeoff for reduction of fractality. The **HPS** approach addresses the ***‹x(i)›*** problem by mapping the inference problem into a different but related one. The approach chooses to deal with CLT-stable process indicators for <x>m x-bar. These robust process indicators are then used to perform repeated hypothesis testing.

To obtain robust indicators, the **HPS** approach tradeoffs lag for process indicator robustness. This decision does not affect the particular domain being addressed…. Explain lag, warm-up, error, delay, overhead, and stability. Theorem on handling of types of signal conditioning cases. Discussion about types of signals in terms of their ergodicity or not and the implications over the robustness of the approach, the definition and theorem needs to be referred or implied or said here. Discuss the timescale and sampling concern (and develop it in more detail in insight or experimental setup). However, to perform hypothesis testing a comparison is needed. The approach is to determine the presence of temporal stability. A temporal stable segment is defined as follows…. Although a temporal stable segment does not necessarily imply a process state, but a process state implies a temporally stable segment. This yields the first condition to infer about the hidden process by performing filtering for temporally stable segments. The statistical filtering must also factor for the wide varying variability that would cause a temporal stable segment not to be a process state. Such sheds insight into why repeated hypothesis testing is not enough to determine the presence of a process state. However, to locate a temporally stable segment, it is not necessary to locate its true beginning and end, it is just necessary to identify its presence. The parameters for the algorithm are therefore implying the timescale of the temporal stability search. This is further examined in detail in Fig. so. To derive the additional process indicator, a similar principle to that of the super-heterodyne [**SHD**] is used to derive an intermediate or reference signal from the signal being examined. Abstractly, in radio receivers, the SHD self-derives a reference signal from which computations against the received signal are done. The principle is similar; a robust stability reference signal is needed in order to determine whether the signal being observed possesses temporal stability w.r.t. the reference signal. Consequently, the reference signal of interest is simply the recent past of the signal we are examining. The question is how much and what past ought to be examined. We address that question in … Need explanation of why the recent past is not being made adaptive nor exploratory nor both. This question is not settled on the experimental examination of the parameter c, for which the performance behavior is the same. This will be true as long as the A random process is weakly stationary if their first moments satisfy …. [**WEAK_STATIONARITY**]. t-test for significantly different means [**T-TEST-NR**] can be modified into a related test, a temporal stability test, where we are interested in determining if two means are significantly close, w.r.t. past historical process performance. To do so, we m Bounded influence function

Mixture function, the sum of unimodal distributions is very often multimodal. The necessariness of these three signals is made evident by comparing the **HPS** monitor operation over a continuous signal and outputting a quantized signal to that of an integer arithmetic unit, which operates over the R and outputs in I but that however it is necessary for full representation that three signals be provided, the integer result, the overflow condition, and the output of residuals. These three signals correspond to the signals of the **HPS** monitor. One may compare the **HPS** monitor to an Integer Arithmetic Unit, which…. as long as variance can be bounded – in this particular setting – across the combined smoothing interval $\boldsymbol{\nu}$ defined as a function of τ. A violation to this would be an discontinuity in ***‹y(i)›***, such as ***‹y(i)›=tan(i)***, a case which upon a delay would be handled as a supra-ordinary statistically significant outlier, discussed shortly. Such would be detected after a finite delay based on the outlier detection unit after a delay Histograms for the PDF for the hidden random process shifts and baseline components. Histogram of the resulting lognormal distribution associated with the CLT addition of non-identical crudely normally distributed on/off sources The input signal ***‹y(i)›*** shown in Fig. XYZ – by definition a lognormal random variable – is stationary in the weak sense [**GRAY:WEAK STATIONARITY]** as all the limiting sampling averages, for each of its first moments, have an upper finite bound [**GRAY:ERGODICITY**]. However, the input signal ***‹y(i)›*** exhibits several localized segments of well-behaved weak stationarity $\boldsymbol{\{\varphi_k\,(\mu_k,\ \sigma_k)\}}$. Such behavior is due to a hidden multimodal random process {X} that, when observed across a sufficiently large time interval, generates an apparent to-be lognormal sampled random variable. This collapse of multimodality into unimodality across sufficiently large time-scales is independent of whether the source constituents of the hidden random process X were scaling distributions or not. This type of time series is referred to as an interrupted time series [**INTERRUPTED TIME SERIES**]. This class of random processes exhibiting segments of weakly stationarity is of particular importance in complex dynamical systems, where such segments represent stable operational process states in the underlying hidden random process being observed. A process state is usually a targeted outcome in a dynamical system modeled by a random process. However, because of its inherent randomness and dynamical nature of the system, the sampled process performance of the system is often instead a series of process states interleaved with the corresponding process transitions between these [**SPC, APC, SPC-APC, MMCN98**]. The generation of log-normal phenomena from mixed ON/OFF (i.e., interrupted) sources has been documented elsewhere [**ETHERNET SELF SIMILAR, MORE NORMAL**], steering research into the study of such heavy tailed distributions [**WEB SELF-SIMILARITY, TEMPORAL STABILITY, FRACTALITY, NETWORK SIMULATIONS, TRAFFIC SHAPING, HEAVY TAIL**]. However, in this paper, we take a different approach by foregoing the analysis of the heavy tailed input time series and focusing on its CLT-stabilized by-products in order to get to the temporal stability. Here is important to observe that an approximation to an infinite variance distribution [**LOGNORMAL**] does not imply that the true but underlying distribution variance is truly unbounded. The approximation is indeed a theoretical model to factor the importance and weight of statistical significant outliers. However, as shown elsewhere, such heavy tail approximations can be the natural consequence of additive but disjoint ***ON/OFF*** sources [**WILLINGER:ONOFFSOURCES**]. As a result, through a timescale artifice, data corresponding to a multimodal hidden random process is effectively being attempted to be modeled by an unbounded (increasing variance) unimodal approximation. This indeed shed insight into the nature of contradictory conclusions and findings that have permeated on the network measurements literature during the past decade [**TEMPORAL STABILITY, NET SIMULATIONS, HEAVY TAIL, SELF SIMILARITY**]. Instead, a long-term outlook at data that appears to be an approximate unimodal (e.g., heavy tailed) distribution could also be examined at smaller timescales and found to be temporally stable at segments and where these segments each could instead be approximated through bounded-variance unimodal (e.g., ***Gaussian***) approximations, resulting in multimodal. This argument in insightful w.r.t. the presence of process states and process shifts in long-term sampling from a hidden random process. This is explicitly illustrated through our experiment setup.

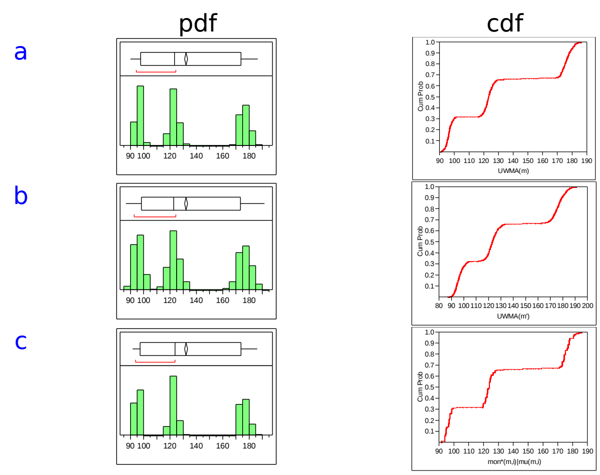

Fig. 35: Histograms (pdf) and cdf for the CLT-stable moving average signals. Part (a) shows the slow signal, part (b) the fast signal, part (c) the online **HPS** monitor.