Sequential Online Volatility Detection For Markov Modulated Asset Price Dynamics

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A fundamental task in financial modeling is that of calibrating asset price models, that is, estimating the parameters of mean return and volatility. Common techniques used to estimate these parameters are based upon maximum likelihood estimation, such as the Expectation Maximisation (EM) algorithm and its variants. These methods can be slow to converge and computationally intensive. Further, in practice, precise estimates of volatilities are often not necessary. For example, in option pricing with Markov modulated volatility models, a 10% error in volatility estimation is usually taken as acceptable.

In this article we suppose that one of M candidate volalility models best explains a given asset price process. Sequential estimators are computed for each of the M candidate models. These schemes compute an estimate for the relative likelihood of a given model explaining an observation process. Two classes of model are considered. In the first model, volatility states are determined by a continuous-time Markov chain. An important practical feature of the detection schemes we compute for this model, is that they do not inlcude stochastic inegration. Here we develop a version of the Clark Transformation [1] based on a Hadamard product, resulting in detector dynamics where the observation process appears as a parameter, rather than an integrator. In the second model, volatility states are determined by a discrete-time Markov chain. Computer simulations for the discrete-time Markov chain models are given on real data for the price evolution of West Texas Crude. These results are compared again an EM algorithm computation for the same data set.

1. Clark, J. M., The Design of Robust Approximations to the Stochastic Differential Equations for Nonlinear Filtering, in J. K. Skwirzynski Ed, Communications Systems and Random Process Theory, Darlington 1977, Alphen aan den Rijn, the Netherlands, Sijthoff and Noorhoff 1978, pp. 721-734.
2. Aggoun, L. and Elliott R. J., Measure Theory and Filtering Cambridge University Press, 2004.