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Toward automatic classification of rockslides in continuous seismic data

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Large rock slope failures often occur without warning and are among the most destructive and dangerous natural events in alpine regions. With growing settlement and development in alpine areas, efficient identification and rapid response to rockslide hazards becomes increasingly critical. Our ultimate goal is near-real-time automated identification of rockslide signals in continuous seismic data, using the network of broadband stations of the Swiss Seismological Service. Even in densely settled Switzerland, large rockslides may go unnoticed for weeks, presenting a number of secondary hazards that rapid event identification from seismic data may help mitigate. Additionally, a complete catalogue of rockslides can aid in the identification of rockslide triggers. Apart from detecting rockslide seismic signals, automatic classification into several event subcategories, e.g. rock falls or rock avalanches, may be feasible. We use the Hidden Markov Toolkit (HTK), originally developed for speech processing, in which the stochastic classifier of hidden Markov models is used to handle the variable signals of rockslides with different volumes or failure processes. Additionally, the approach used in this study allows to create an event model using only a single rockslide seismic signal and some hours of background noise recording. As large rockslides are a rare occurrence, we are thus independent of previously acquired training samples. The event model is constructed from a set of feature vectors extracted from the seismic signal in both the time and frequency domains, e.g. signal envelope, dominant frequency or bandwidth. To classify an unknown event, the probability of a section of seismic data being an event, relative to the probability of being noise, is then computed. We have assembled a set of 36 basis features that we compute in different frequency bands, leading to a total pool of 289 different features. From this pool we select at most 30 independent features for model construction. In preliminary tests with the resulting event model, we have automatically classified nearby rockslides and some large distant rockslides. Event onset times were identified within one second or less. Re-training the event model with different rockslide events and selecting a different subset of features may result in improved classification results.