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Health indicator learning for predictive maintenance based on a triplet loss and deep siamese network

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The remaining useful life (RUL) prediction of a system often relies on the knowledge of a health indicator (HI). Yet, HI acquisition may be hindered by a limited knowledge of the system degradation process, encouraging one to resort to monitored data instead [1].

The classical data-driven approach for HI construction is to compute one or several statistical features on a monitored signal and considering this feature, or an aggregation of them, as the HI [7, 8]. It therefore relies on either expert knowledge or brute-force testing of multiple combination of statistical features. Hence, the limits of these approaches are threefold: the number of statistical features to test can rapidly become overwhelming, the approach is application-dependent and there is no guarantee of scale-similarity across the data-set. These limits come in addition to the challenge of getting a HI with a monotonous trend, and no abrupt changes. To alleviate these drawbacks, approaches based on deep learning have emerged, especially supervised ones e.g. [2, 3, 4]. These methods have the advantages of being more general, enabling the inference of HI on raw data and enforcing the scale-similarity. Nevertheless, to the best of the authors' knowledge, these approaches do not ensure the monotonicity of the HI despite of the well acknowledged importance of this property [1]. Also, the use of supervised learning with labels corresponding to RUL [5, 2, 4] usually assumes an unverified hypothesis: the degradation process linearity.

In this work, the goal is to propose a general method for learning a HI from monitored time series, that fits a monotonous degradation, without any hypothesis on its particular form. For this purpose, an unsupervised metric learning approach based on a deep siamese network and triplet loss [6] is used. First the entire available run-to-failures time series are split into small samples. Then each sample is converted into a time-frequency image with the continuous wavelet transform. To fit the model, triplets of sample images are passed into a convolutionnal siamese neural network and then, in pairs, through a distance layer. The network is optimized by the triplet loss, which enforces the distance minimization between neighbor samples, while maximizing the distance between remote ones. By choosing the triplets based on the known distance of the samples with relation to their time of acquisition, the model favors the learning of a distance metric that can be used to construct a HI. To enforce the monotonicity, a penalization component is added to the loss, that relies on a quadruplet instead of a triplet, with two remote samples from the anchor instead of one: one in the future and one in the past. These techniques are applied on two problems where a degradation process needs to be monitored via a HI: A toy example based on a simple simulated crack growth model and a multivariate application on the health prognosis of ball bearings estimated on a publicly available dataset.

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