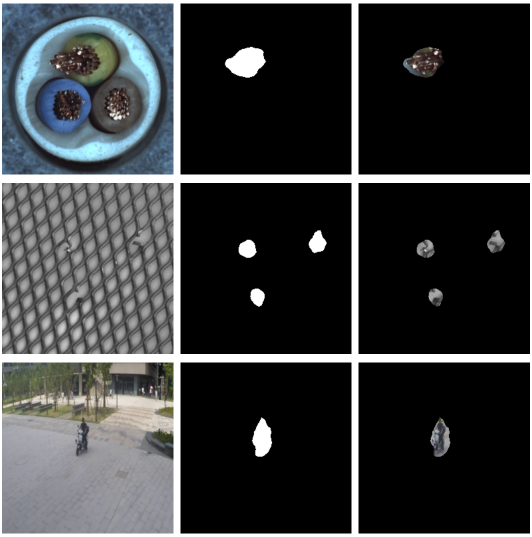

Fig. 3. (top rows) Anomaly detection on images from the Cable and Grid categories of the MVTec dataset (bottom) Detecting bike anomaly on the STC dataset.

the higher levels on their own results in diminished performance (due to lower resolution). Using a combination of all features in the pyramid results in the best performance. In Tab. 7, we compared using the top K neighboring normal images as performed by our first stage vs. choosing them randomly from the dataset. We observe that choosing the kNN images improves performance. This does not affect all classes equally. As an example, we report the numbers for the class "Grid" which has much variation between images. For this category, using the kNN images results in much better performance than randomly choosing K images.

5 Discussion

Anomaly detection via alignment: Most current sub-image anomaly detection methods take the approach of learning a large parametric function for auto-encoding images, making the assumption that anomalous regions will not be reconstructed well. Although this approach does achieve some success, we take a much simpler approach. Similarly to image alignment methods and differently from other sub-image anomaly detection methods, our method does not require feature training and can work on very small datasets. A difference between our method and standard image alignment is that we find correspondences between the target image and parts of K normal images, as opposed to an entire single normal image in simple alignment approaches. The connection with alignment methods, can help in speeding up our method e.g. by combining it with the