

Sketch-a-Net that Beats Humans

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Sketches are very intuitive to humans and have long been used as an effective communicative tool. With the proliferation of touchscreens, sketching has become a much easier undertaking for many – we can sketch on phones, tablets and even watches. However, recognising free-hand sketches (e.g. asking a person to draw a car without any instance of car as reference) is an extremely challenging task. This is due to a number of reasons: (i) sketches are highly iconic and abstract, e.g., human figures can be depicted as stickmen; (ii) due to the free-hand nature, the same object can be drawn with hugely varied levels of detail/abstraction, e.g., a human figure sketch can be either a stickman or a portrait with fine details depending on the drawer; (iii) sketches lack visual cues, i.e., they consist of black and white lines instead of coloured pixels. A recent large-scale study on 20,000 free-hand sketches across 250 categories of daily objects puts human sketch recognition accuracy at 73.1% [2], suggesting that the task is challenging even for humans.

Prior work on sketch recognition generally follows the conventional image classification paradigm, that is, extracting hand-crafted features from sketch images followed by feeding them to a classifier. Most hand-crafted features traditionally used for photos (such as HOG, SIFT and shape context) have been employed, which are often coupled with Bag-of-Words (BoW) to yield a final feature representations that can then be classified. However, existing hand-crafted features designed for photos do not account for the unique abstract and sparse nature of sketches. Furthermore, they ignore a key unique characteristics of sketches, that is, a sketch is essentially an ordered list of strokes; they are thus sequential in nature (See Fig 1). In contrast with photos that consist of pixels sampled all at once, a sketch is the result of an online drawing process. It had long been recognised in psychology that such sequential ordering is a strong cue in human sketch recognition, a phenomenon that is also confirmed by recent studies in the computer vision literature [7]. However, none of the



Figure 1: Illustration of stroke ordering in sketching with the Alarm Clock category. Each sketch is split into three parts according to stroke ordering.

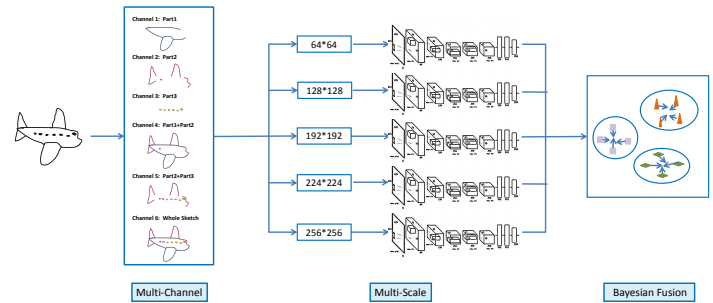


Figure 2: Illustration of our overall framework.

existing approaches attempted to embed sequential ordering of strokes in the recognition pipeline even though that information is readily available.

In this paper, we propose a novel deep neural network (DNN), Sketch-a-Net (See Fig 2), for free-hand sketch recognition, which is specifically designed to accommodate the unique characteristics of sketches including multiple levels of abstraction and being sequential in nature. Our contributions are summarised as follows: (i) for the first time, a representation learning model based on DNN is presented for sketch recognition in place of the conventional hand-crafted feature based sketch representations (Details are listed in Table 1); (ii) we demonstrate how sequential ordering information in sketches can be embedded into the DNN architecture and in turn improve sketch recognition performance; (iii) we propose a multi-scale network ensemble that fuses networks learned at different scales together via joint Bayesian fusion [1] to address the variability of levels of abstraction in sketches. Extensive experiments on the largest hand-free sketch benchmark dataset, the TU-Berlin sketch dataset [2], show that our model significantly outperforms existing approaches and can even beat humans by 1.8% at sketch recognition (See Table 2).

Index	Layer	Type	Filter Size	Filter Num	Stride	Pad	Output Size
0		Input	-	-	-	-	225 × 225
1	L1	Conv	15 × 15	64	3	0	71 × 71
2		ReLU	-	-	-	-	71 × 71
3		Maxpool	3 × 3	-	2	0	35 × 35
4	L2	Conv	5 × 5	128	1	0	31 × 31
5		ReLU	-	-	-	-	31 × 31
6		Maxpool	3 × 3	-	2	0	15 × 15
7	L3	Conv	3 × 3	256	1	1	15 × 15
8		ReLU	-	-	-	-	15 × 15
9	L4	Conv	3 × 3	256	1	1	15 × 15
10		ReLU	-	-	-	-	15 × 15
11	L5	Conv	3 × 3	256	1	1	15 × 15
12		ReLU	-	-	-	-	15 × 15
13		Maxpool	3 × 3	-	2	0	7 × 7
14	L6	Conv(=FC)	7 × 7	512	1	0	1 × 1
15		ReLU	-	-	-	-	1 × 1
16		Dropout (0.50)	-	-	-	-	1 × 1
17	L7	Conv(=FC)	1 × 1	512	1	0	1 × 1
18		ReLU	-	-	-	-	1 × 1
19		Dropout (0.50)	-	-	-	-	1 × 1
20	L8	Conv(=FC)	1 × 1	250	1	0	1 × 1

Table 1: The architecture of Sketch-a-Net.

HOG-SVM [2]	Ensemble [5]	MKL-SVM [6]	FV-SP [7]	Human [2]
56%	61.5%	65.8%	68.9	73.1%
AlexNet-SVM [3]	AlexNet-Sketch [3]	LeNet [4]	Sketch-a-Net	
67.1%	68.6%	55.2%	74.9%	

Table 2: Comparison with state of the art results on sketch recognition

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