BÖLÜM 1

GÖRÜNTÜ İŞLEME TABANLI ÜRETKEN ÇEKİŞMELİ AĞ MODELLERİ

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GİRİŞ

Görüntü işleme, bilgisayarla görme, bilgisayar grafiklerindeki birçok problemde amaç bir girdi görüntüsüne karşılık çıktı üretmektir. Bir girdi görüntüsüne karşılık üretilebilecek pek çok çıktı mevcuttur. Bir kavram, farklı dillerde ifade edilebildiği gibi bir görüntü kenar haritası, anlamlı bölütleme, nesne haritası vb. şeklinde ifade edilebilir. Bu işlemler görüntüden görüntüye dönüşüm problemi olarak adlandırılmaktadır. Bu dönüşümlerin her biri farklı yöntemler (1-6) kullanılarak gerçekleştirilmektedir. Genel olarak bakıldığında bu dönüşüm işlemleri hep benzer (pikselden piksele dönüşüm) işlemlerdir.

Günümüzde imge dönüştürme ve sınıflandırma işlemlerinde evrişimsel sinir ağları (ESA) kullanılarak belirgin adımlar atılmıştır. ESA'lar bir kayıp fonksiyonunu minimuma indirgemeyi öğrenirler. Görüntü temelinde bakıldığında, tahmin edilen piksel değeri ile gerçek piksel değeri arasındaki hata minimize edilmeye çalışılmaktadır. Bu durum, bulanık çıktıların üretilmesine neden olmaktadır. Bunun temel sebebi tüm olası çıktı değerlerini ortalamak suretiyle, kayıp fonksiyonunun çıktısını en aza indirgemeye çalışılmasından kaynaklanmaktadır. Bu nedenle, ESA'ları kullanarak keskin foto gerçekçi görüntüler üretmek açık bir problem alanıdır.

Bir kayıp fonksiyonunu minimize etmek yerine "çıktı imgesini gerçeklikten ayırt edilemez" gibi üst düzey bir hedef belirlenirse amaca uygun bir kayıp fonksiyonu öğrenilebilir ve bu yöntem birçok benzer problemde kullanılabilir. Yakın zamanda önerilen üretken çekişmeli ağlar (generative adversarial networks) (7)

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