Benefits of coherent demodulation for eavesdropping on HDMI emissions

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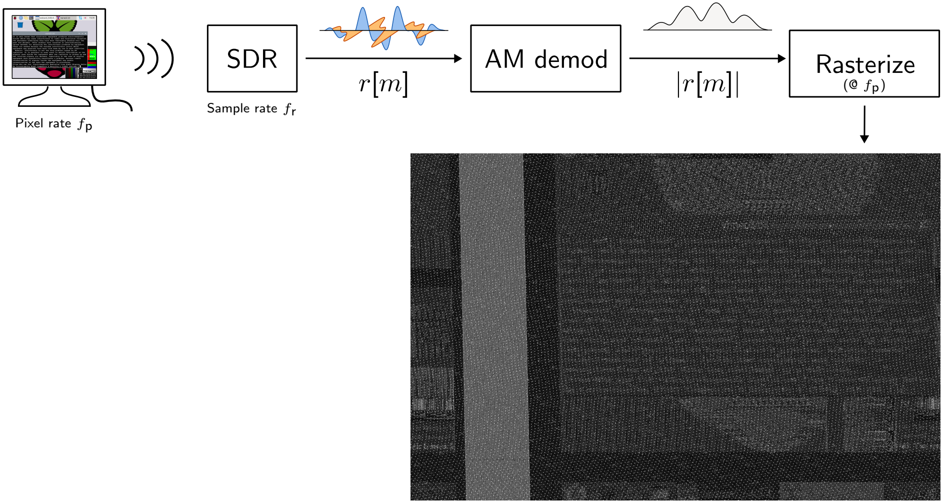
A typical TEMPEST attack



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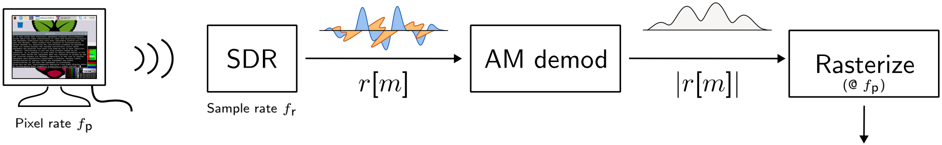
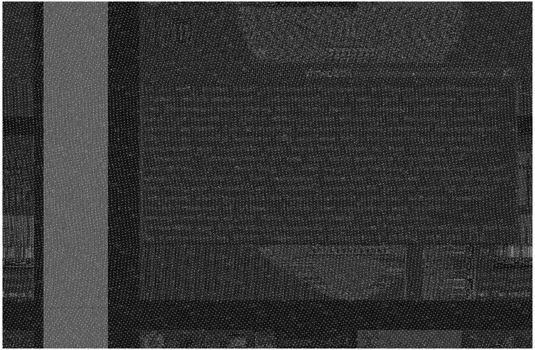
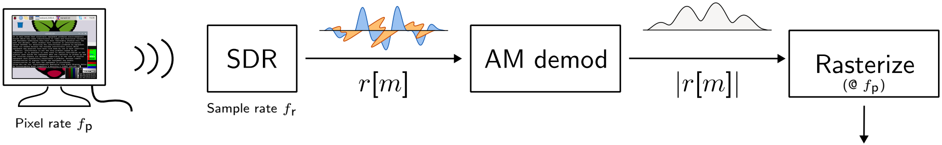


- Estimate pixel rate f_p, e.g. from the autocorrelation $R_{r,r}[d] = \sum_m r[m] \cdot r[m+d]^*$:

$$\hat{d} = \operatorname*{argmax}_{f_{\mathsf{v},\perp} \leq f_\mathsf{r}/d \leq f_{\mathsf{v},\top}} |R_{r,r}[d]|^2$$

$$f_\mathsf{p} \approx f_\mathsf{r} \cdot \frac{w_\mathsf{t} h_\mathsf{t}}{\hat{d}}$$





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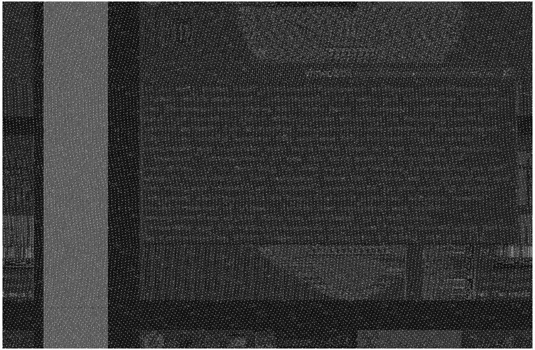
- Resample to $f_\mathsf{s} = k \cdot f_\mathsf{p}$ for $k \in \mathbb{N}$



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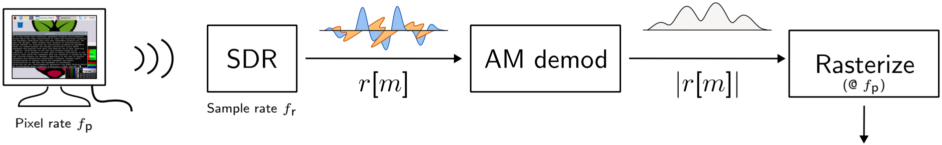

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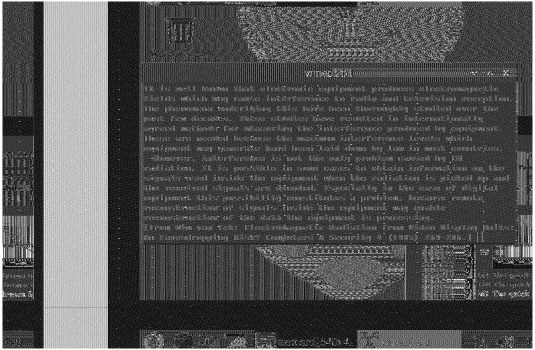
- Resample to $f_\mathrm{s} = k \cdot f_\mathrm{p}$ for $k \in \mathbb{N}$
- Average several rasterized frames



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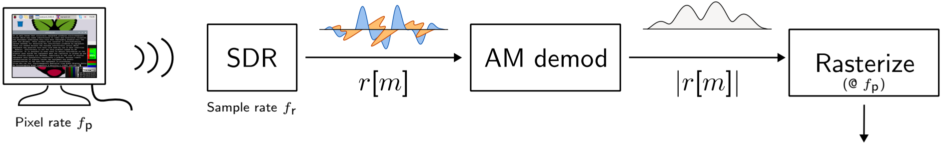

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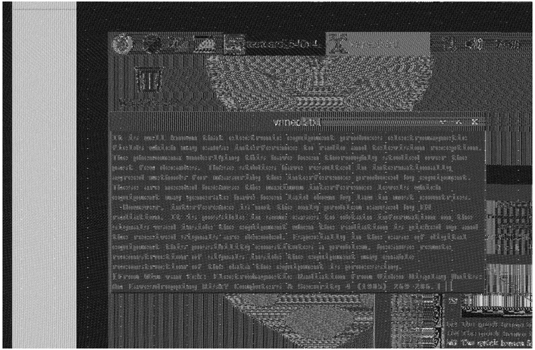
$$\hat{d} = \underset{f_{v,\perp} \leq f_r/d \leq f_{v,\top}}{\text{argmax}} |R_{r,r}[d]|^2$$

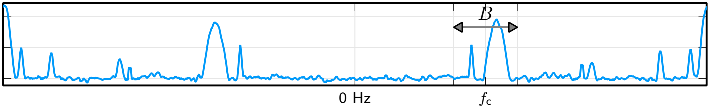
$$f_p \approx f_r \cdot \frac{w_t h_t}{\hat{d}}$$

- Resample to $f_s = k \cdot f_p$ for $k \in \mathbb{N}$
- Average several rasterized frames
- Align image

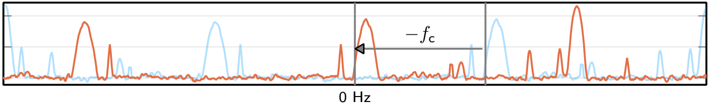


Software-defined radio receiver

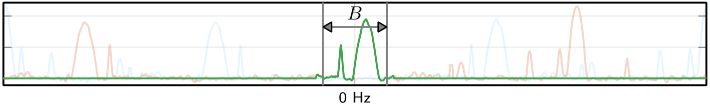
Antenna waveform (shown as Fourier spectrum) $s_0(t)$:



Downconvert: $s_d(t) = s_0(t) \cdot e^{-2\pi j f_c t}$



Lowpass filter: $s_f(t) = \int s_d(t-\tau)g(\tau)d\tau$



Finally, output sampled $r[m] = s_f(m/f_r)$.

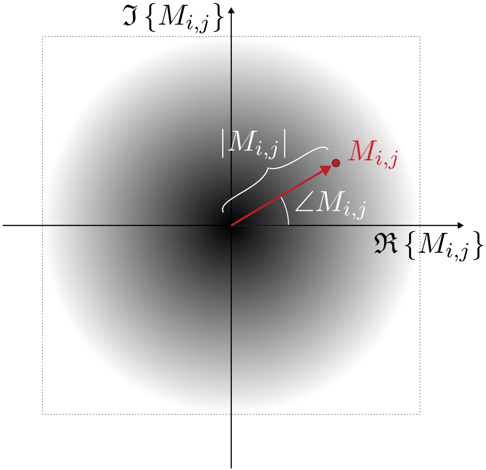
Rasterizing complex-valued signals: amplitude demodulation

Most eavesdropping demonstrations amplitude demodulate samples $M_{i,j} \in \mathbb{C}$ and visualise them as grayscale pixels.

For example, mapping 1% and 99% quintiles to black and white:

$$\text{Gray}\left(\frac{|M_{i,j}| - q_{1\%}}{q_{99\%} - q_{1\%}}\right)$$

This discards phase information $\angle M_{i,j}$.

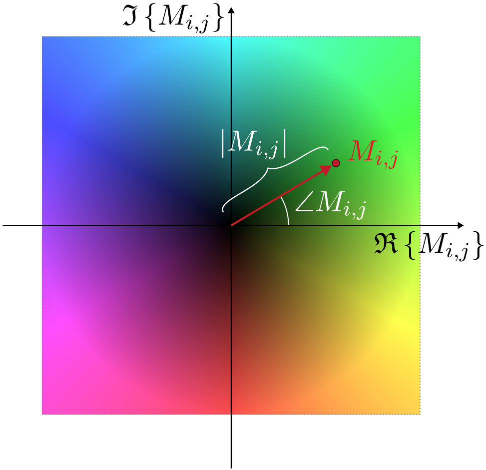


Rasterizing complex-valued signals: HSV visualisation

Using the HSV (hue, saturation, value) colour space allows us to also show the phase:

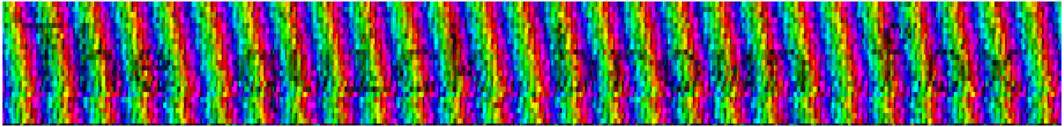
$$\mathsf{HSV}\left(\angle M_{i,j},\ S,\ \frac{|M_{i,j}| - q_{1\%}}{q_{99\%} - q_{1\%}}\right)$$

(We leave the saturation coordinate S as a user preference.)

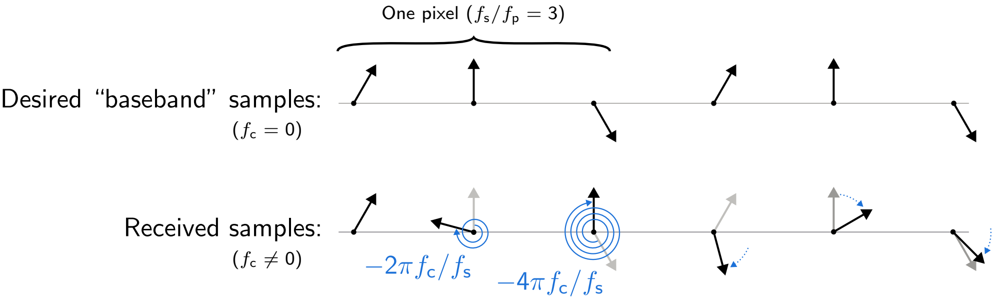


First rasterization attempt

Directly rasterizing an SDR-received signal produces a "rainbow-banding" image:

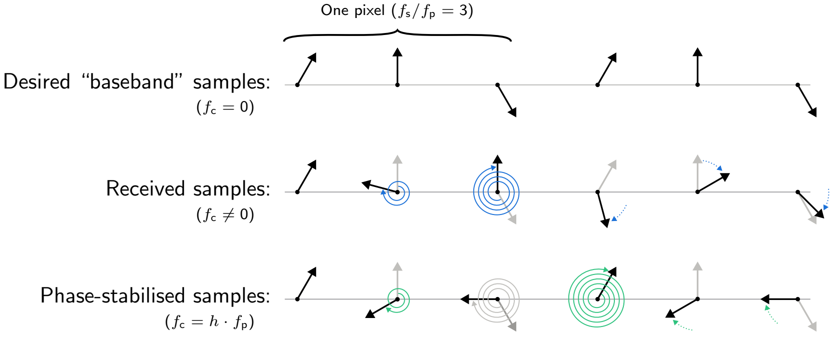


This is due to SDR downconversion from the antenna waveform $s_0(t)$ to $\mathrm{e}^{-2\pi \mathrm{j} f_\mathrm{c} t} \cdot s_0(t)$.



Obtaining consistent phase angles

Shift the centre frequency to a harmonic $h \cdot f_\mathrm{p}$ of the pixel frequency:



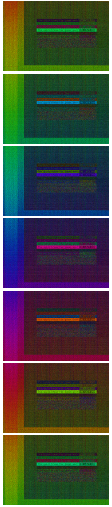
We combine frequency shifting $f_\mathrm{c} \to h \cdot f_\mathrm{p}$ with resampling to $f_\mathrm{s} = k \cdot f_\mathrm{p}$:

$$s[n] \approx s_\mathrm{f}\left(\frac{n+\lambda}{f_\mathrm{s}}\right) \cdot \mathrm{e}^{2\pi(f_\mathrm{c}-hf_\mathrm{p})n/f_\mathrm{s}}$$

Obtaining consistent phase angles

Some drift still remains over longer intervals.

Coherent averaging requires consistent phase across many frames, i.e. a more accurate f_{p} estimate.



Accurate f_p estimation

We improve the f_p estimate several times until convergence, by iterating over three steps:

1. Resampling and frequency-shifting $f_c \to h \cdot f_p$:

$$s[n] \approx s_f\left(\frac{n+\lambda}{f_s}\right) \cdot e^{2\pi(f_c - h f_p)n/f_s}$$

2. Computing the autocorrelation:

$$R_{s,s}[d] = \sum_n s[n] \cdot s[n+d]^*$$

3. Updating the f_p estimate, with a fine-tuning term which measures phase drift between frames:

$$f_p := f_p \cdot \left(\frac{k w_t h_t}{\hat{d}} + \frac{k \angle R_{s,s}[\hat{d}]}{2\pi h \hat{d}}\right)$$

(This is a corrected version of Eqn. 11 in the proceedings)

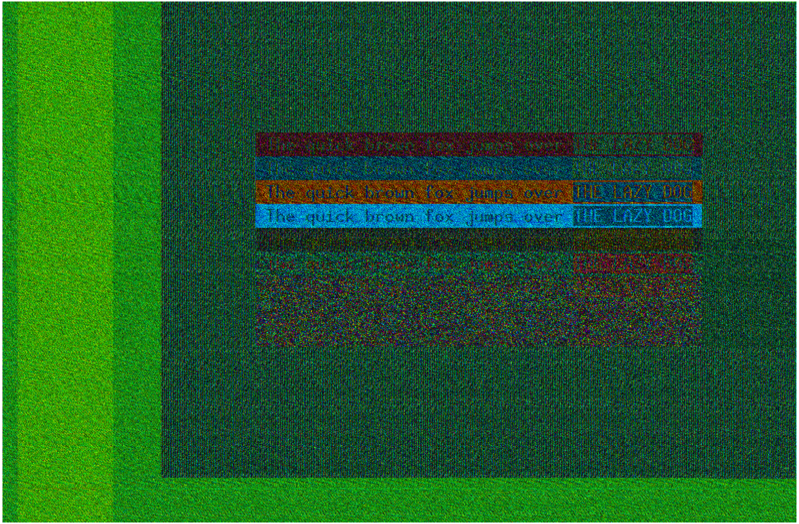
Iterations	f_p
0	25.200000000 MHz
1	25.200096064 MHz
2	25.200096764 MHz
3	25.200096794 MHz
4	25.200096793 MHz
5	25.200096788 MHz
6	25.200096788 MHz

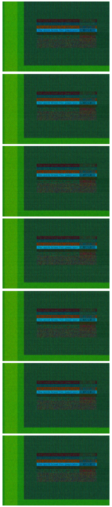
$$\hat{d} = \underset{f_{v,\perp} \le f_r/d \le f_{v,\top}}{\operatorname{argmax}} |R_{s,s}[d]|^2$$

In later iterations, we can also search for the correlation peak at larger multiples of the frame period.

Obtaining consistent phase angles (with accurate f_p)

With the more accurate f_p, the phase now stays consistent across frames.

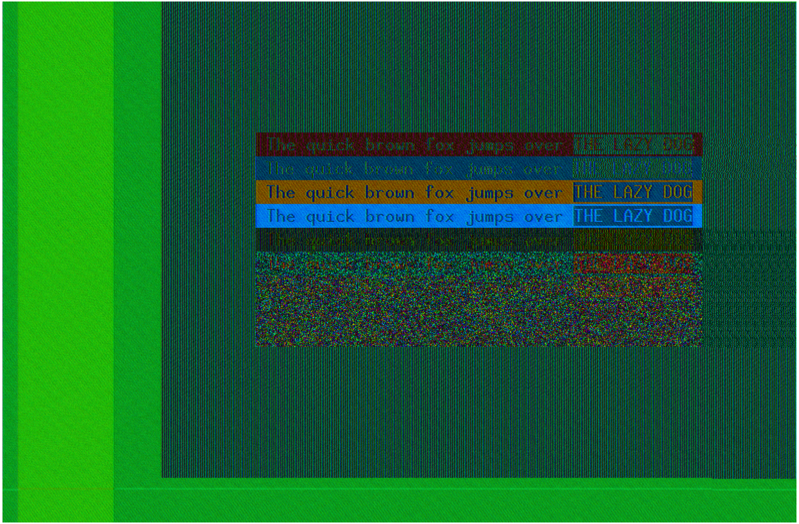




Consistent phase angles enable coherent averaging

We can now periodically average unrotated $M_{i,j} \in \mathbb{C}$ to reduce noise.

This image was rasterized from 30 averaged frames ($\approx$ 0.5 s long).



Does the phase provide new information?

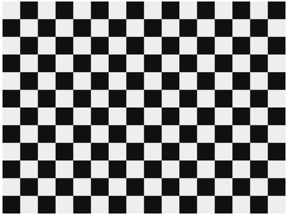
To demonstrate how phase information can help with distinguishing colours, we used a test image with two grayscale colours: #101010 and #eeeeee.

These are TMDS-encoded in HDMI as complementary bit sequences:

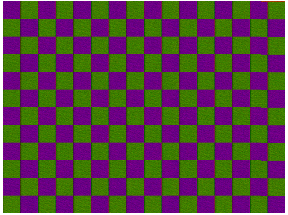
- #101010 → 0111110000
- #eeeeee → 1000001111

The resulting emissions therefore differ only in their sign.

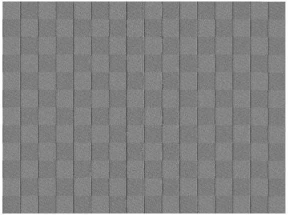
Displayed:



Coherently demodulated:



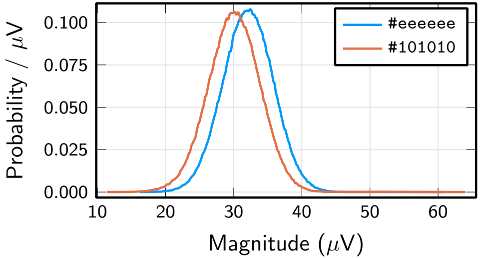
Amplitude demodulated:



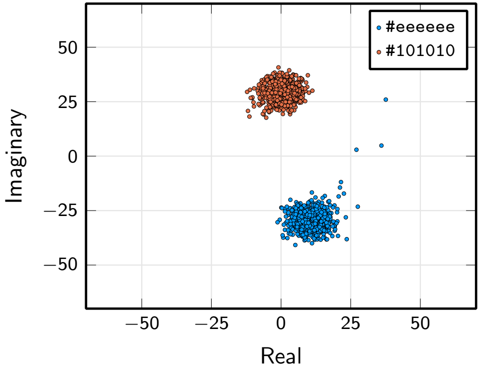
Does the phase provide new information?

The distributions of amplitudes $|M_{i,j}|$ for these two colours overlap significantly, while those for the full $M_{i,j} \in \mathbb{C}$ do not:

Amplitude distribution ($|M_{i,j}|$):



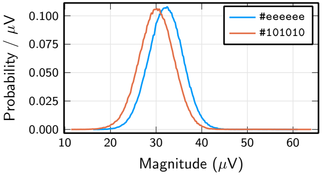
Complex distribution ($M_{i,j}$):



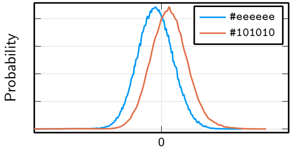
Comparing distributions using dimensionality reduction

We can better distinguish colours by combining information from all $k = 3$ samples for a pixel with dimensionality reduction, e.g. using Principal Component Analysis (PCA).

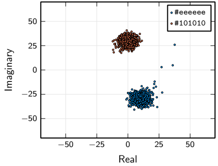
Amplitude demodulation (3-dimensional PCA on $|M_{i,3j}|, |M_{i,3j+1}|, |M_{i,3j+2}|$):



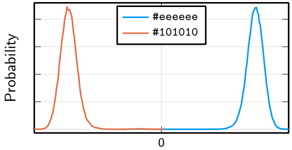
PCA →



Coherent demodulation (6-dimensional PCA on $\Re\{M_{i,3j}\}, \Im\{M_{i,3j}\}, \ldots, \Im\{M_{i,3j+2}\}$):



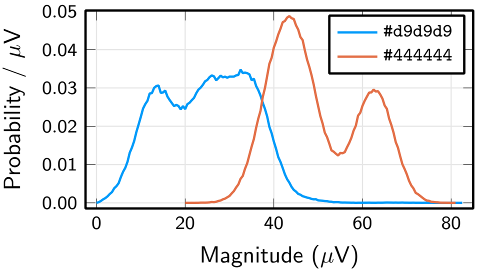
PCA →



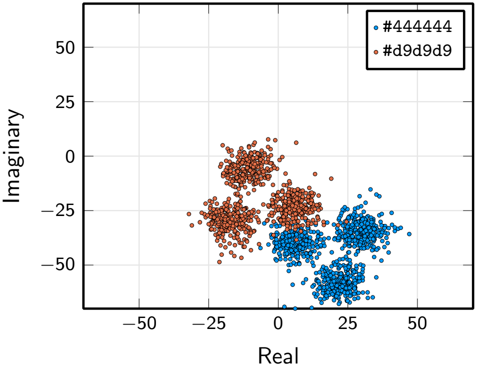
A more complex encoding

For another randomly chosen pair of colours, their more varied TMDS encodings result in different distributions for each sample position in a pixel:

Amplitude distribution ($|M_{i,j}|$):



Complex distribution ($M_{i,j}$):

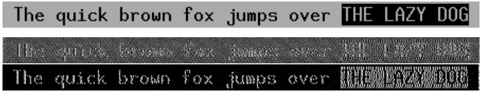


PCA-based rasterization

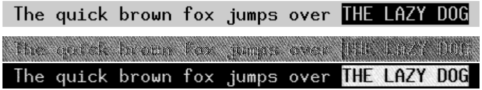
Rasterizing the projection on the largest-eigenvalue PCA vector can produce grayscale images with better contrast than amplitude demodulation.

❶ Black and white:

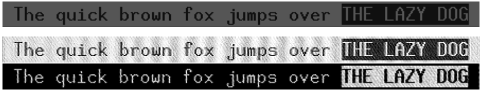
❷ Maximum bit transition contrast:



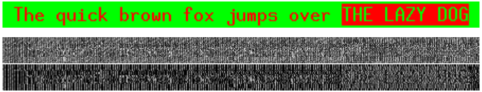
❸ Complementary TMDS encoding:



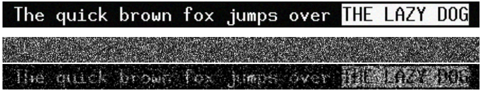
❹ Maximum contrast if AM demodulated:



❺ Minimum contrast if AM demodulated:



❻ Low nibble random:



(Top to bottom: displayed, amplitude demodulated, PCA)

Summary

- Phase information can be included in the rasterized image as hue in the HSV colour space
- Shifting the centre frequency precisely to a harmonic of the pixel clock stabilises phase and allows periodic averaging in the complex domain
- We can precisely estimate the target's pixel-clock frequency using both position and phase of the peak of the complex-valued autocorrelation sequence
- Preserving phase information helps better discriminate between colours
- With multiple samples per pixel, dimensionality reduction can further improve contrast