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MKID digital readout tuning with deep learning

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ABSTRACT

Microwave Kinetic Inductance Detector (MKID) devices offer inherent spectral resolution, simultaneous read out of thousands of pixels, and photon-limited sensitivity at optical wavelengths. Before taking observations the readout power and frequency of each pixel must be individually tuned, and if the equilibrium state of the pixels change, then the readout must be retuned. This process has previously been performed through manual inspection, and typically takes one hour per 500 resonators (20 h for a ten-kilo-pixel array). We present an algorithm based on a deep convolution neural network (CNN) architecture to determine the optimal bias power for each resonator. The bias point classifications from this CNN model, and those from alternative automated methods, are compared to those from human decisions, and the accuracy of each method is assessed. On a test feed-line dataset, the CNN achieves an accuracy of 90% within 1 dB of the designated optimal value, which is equivalent accuracy to a randomly selected human operator, and superior to the highest scoring alternative automated method by 10%. On a full ten-kilopixel array, the CNN performs the characterization in a matter of minutes — paving the way for future mega-pixel MKID arrays.

1. Introduction

Microwave Kinetic Inductance Detectors, or MKIDs, are a superconducting pair-breaking detector (Day et al., 2003) that operate across the electromagnetic spectrum in different variations such as: Catalano et al. (2016) (microwave) Yates et al. (2011) (far-IR), Mazin et al. (2012) (UV, optical, near-IR), and Ulbricht et al. (2015) (X-ray). UV, optical, near-IR (UVOIR) MKIDs are photon counting detectors with spectral resolution $R = \lambda/\Delta\lambda \sim 10$ at 1 μm, enabling read-noise free (photon limited), low-resolution spectroimaging without filters or dispersive optics. Compared to other cryogenic detectors, these devices are simple to fabricate and operate, as thousands of these pixels are read out per feed-line using warm electronics. The first MKID camera (ARCONS), when commissioned in 2011, was the largest non-dispersive optical/near-infrared integral field spectrograph fielded by a factor of ten (Mazin et al., 2013; Szypryt et al., 2014; Strader et al., 2016). The current generation of UVOIR MKID devices are up to 20,000 pixels (Meeker et al., 2015), and larger arrays are planned (Marsden et al., 2013). The pixel format of MKIDs in the sub-millimetre and far-infrared are also several kilopixels (Adam et al., 2018) and systems capable of reading out 10^4 pixels have been demonstrated (Baselmans et al., 2017). These large formats make MKIDs a competitive detector technology for high contrast imaging of exoplanets (Meeker et al., 2015), long slit spectroscopy (O'Brien et al., 2014), as well as security and biomedical applications (Jonge et al., 2012).

In order to read out an MKID array, the digital readout system must be tuned for each pixel. Biasing a kilopixel array by manual inspection can take several hours, and is prone to inconstancies between users and human error. Existing approaches for automating this task perform poorly on resonators that are non-ideal, as we will demonstrate in Section 3. We present a machine learning-based package for tuning the bias points for an MKID readout prior to observations. This algorithm has been used to set up the MKID-based high contrast imager-DARKNESS (Meeker et al., 2015) for each of the four observing runs at the Palomar Observatory. This package should be beneficial to any system where biasing many resonators will be required such as: phonon-mediated detectors for neutrinoless double beta-decay or dark matter interactions (Martinez et al., 2017) and frequency multiplexed quantum processors (George et al., 2017).

This manuscript will be structured as follows: In Section 2 we introduce our devices, describe our measurement, and outline the traditional strategies for automated biasing of individual MKIDs. In Section 3 we discuss the various pathologies that can affect

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resonators and show how the standard ways of automated biasing fail when applied to these scenarios. In Section 4 we present our machine-learning model and in Section 5 we compare the results of the machine-learning model to two alternative automated algorithms and the manual inspection method. In Section 6 we end with the conclusions and future prospects.

2. Resonator bias tuning

An MKID device is made from a superconducting film, lithographically patterned into an array of microwave resonators. Modern UVOIR resonators use lumped element designs and thousands are coupled to a single transmission line (see Fig. 1) but other geometries (see Zmuidzinas, 2012 review) are equivalent for the purposes of this paper. The complex transmission $S_{21}(\omega) = I(\omega) + iQ(\omega)$ (where I and Q are the in-phase and quadrature components) is a measure of the forward voltage gain across an electrical component. When a probe tone is swept in frequency (ω) across the resonance, the scalar transmission $|S_{21}|$ is minimized at the resonant frequency and is mostly unattenuated off-resonance. Fig. 1d shows a subsection of a broadband frequency sweep across a 2000 pixel feed-line, where each dip represents a single resonator with quality factor $Q_r \approx 10^5$.

Fig. 2 shows the transmission through the device at frequencies ±450 kHz of the resonant frequency of a single MKID pixel at a range of readout powers. The lowest power sample is approximately −70 dBm. This type of measurement is hereafter termed a resonator powersweep. At low power the I and Q components trace a continuous resonance loop in the complex plane and a continuous dip in the transmission spectrum. At higher powers the resonator exhibits a nonlinear response as a function of driving current, and given sufficient power, the resonator bifurcates into two quasi-stable states, which manifest as a discontinuity close to the resonant frequency (Swenson et al., 2013; Thomas et al., 2015). In this bifurcation regime the resonator is rendered non-functional for photon detection (Strader, 2016).

To read out an MKID pixel, we measure the phase of the transmission at the equilibrium resonant frequency. To optimize the signal-to-noise ratio on this measurement we need to drive the resonators as powerfully as possible to reduce the contribution from the cryogenic amplifier (typically a High-electron-mobility transistor) noise and the effect from Two Level System (TLS) noise (Gao, 2008). Therefore, to bias a given resonator, the power at which the resonator first bifurcates is identified, and the power 2 dB below this value is chosen. This method is the primary criterion of this manuscript and will hereafter be referred to as Rule #1.

It has been shown by de Visser et al. (2010) that overpowering resonators can be detrimental to device sensitivity because of the increase in generation-recombination noise from readout power heating, while Swenson et al. (2013) have shown that in certain circumstances there could be benefits from operating in the non-linear regime. Ultimately, optimal operating point of a given resonator will depend on several factors such as material, geometry, quality factor and the wavelength of incident light (since UVOIR MKID detectors are not currently limited by generation-recombination noise). This manuscript will assume that sensitivity is maximized by applying Rule #1 (along with the exceptions related to pathologies described later). An investigation into sensitivity optimization of UVOIR MKIDs is saved for later studies.

2.1. Analytical method

From Khalil et al. (2012), the complex transmission of a resonator, driven in the low power regime, coupled to a transmission line with mismatched input and output impedances, can be described by an asymmetric Lorentzian

$$S_{21}(x_0) = g(x_0)e^{i\phi(x_0)}\left[1 - \frac{\frac{Q_r}{Q_c}\left(1 + 2jQ_r\frac{\delta\omega}{\omega_0}\right)}{1 + 2jQ_r x_0}\right], \quad (1)$$

where the gain $g(x) = g_0 + g_1 x$ and phase $\phi(x) = \phi_0 + \phi_1 x$ factors have been included to account for scaling and orientation of the resonance loop due to, e.g., the length of the transmission line. Q_c is the coupling quality factor, Q_i is the internal quality factor and Q_r is the total quality factor with $Q_r^{-1} = Q_i^{-1} + Q_c^{-1}$. $\delta\omega$ is a frequency offset applied to the resonance to account for any impedance mismatch between the resonator and feed-line (Geerlings, 2013). In the low power regime, the fractional detuning of the sampling frequency ω is

$$x_0 = \frac{\omega - \omega_{r,0}}{\omega_{r,0}}, \quad (2)$$

where $\omega_{r,0}$ is the resonance. If a powersweep measurement contains a pair of colliding resonators, then the fitting function becomes the summation of two asymmetric Lorentzians and the number of free parameters in Eq. (1) is doubled.

In the high power regime the nonlinearity of superconducting resonators can be attributed to quasiparticle heating by readout photons (Thomas et al., 2015), or an intrinsic property of the kinetic inductance of superconductors at high current (Swenson et al., 2013; Semenov et al., 2016). The resonators in this manuscript will be analysed in the context of the latter model because there is no major degradation of Q_i at higher powers as expected with the quasiparticle-heating model. To account for the distortion of the S_{21} profile in the nonlinear regime, the fractional detuning becomes

$$x = x_0 + \frac{a}{1 + 4Q_r^2 x^2}, \quad (3)$$

where a is the nonlinearity parameter

$$a = \frac{2Q_r^3 P_r}{Q_c \omega_r E_*}, \quad (4)$$

where P_r is the readout power and E_* is the scaling energy from the nonlinearity.

SCRAPS is a superconducting resonator analysis package (Carter et al., 2017). We used this tool to fit Eq. (1) to the measured I and Q data of a resonator powersweep. Then, the resulting values for nonlinearity parameter a were used to identify the first bifurcation power, and with Rule #1, an estimate for the optimal bias point was inferred. This analytical method will hereby be referred to as 'AM'.

2.2. Numerical method

If the primary concern is the degree of bifurcation then a very simple but effective metric is to monitor the separation between the I, Q magnitudes at adjacent frequencies, here termed IQ velocity. At a single readout power, it is defined as

$$v_{IQ}(f) = \sqrt{[Q(f) - Q(f-1)]^2 + [I(f) - I(f-1)]^2}, \quad (5)$$

where f is the frequency index and $(f-1)$ is the previous frequency index. When a discontinuity forms during bifurcation there is a large spike in the v_{IQ} spectrum at the discontinuity frequency, and at the adjacent frequencies the v_{IQ} should remain minimal. High Q_r resonators will show large values of v_{IQ} due to the larger relative frequency sampling compared to the resonator width. However, the v_{IQ} of the adjacent frequencies will also be large. To distinguish spikes in v_{IQ} caused by a high Q_r from that of a discontinuity, the